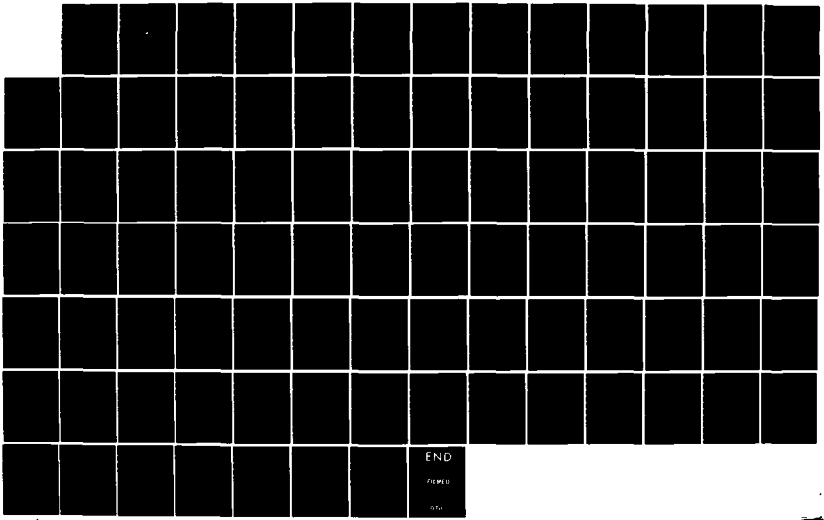
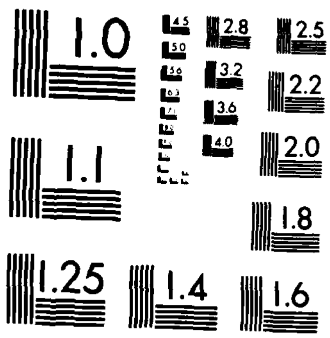
AD-A155 034 FORECASTING OF TROPICAL CYCLONE MOTION USING AN EOF (EMPIRICAL ORTHOGONAL FUNCTION) REPRESENTATION OF WIND FORCING(U) NAVAL POSTGRADUATE SCHOOL MONTEREY CA 1/1

UNCLASSIFIED W E WILSON DEC 84 F/G 4/2 NL





MICROCOPY RESOLUTION TEST CHART
NATIONAL BUREAU OF STANDARDS-1963-A

2

NAVAL POSTGRADUATE SCHOOL
Monterey, California

AD-A155 034

DTIC
ELECTE
JUN 17 1985
S D
B

DTIC FILE COPY

THESIS

FORECASTING OF TROPICAL CYCLONE MOTION
USING AN EOF REPRESENTATION OF WIND FORCING

by

William Earle Wilson

December 1984

Thesis Advisor: R. L. Elsberry

85 5 24 177

SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)

REPORT DOCUMENTATION PAGE		READ INSTRUCTIONS BEFORE COMPLETING FORM
1. REPORT NUMBER	2. GOVT ACCESSION NO.	3. RECIPIENT'S CATALOG NUMBER
4. TITLE (and Subtitle) Forecasting of Tropical Cyclone Motion Using an EOF Representation of Wind Forcing		5. TYPE OF REPORT & PERIOD COVERED Master's Thesis December 1984
		6. PERFORMING ORG. REPORT NUMBER
7. AUTHOR(s) William Earle Wilson		8. CONTRACT OR GRANT NUMBER(s)
9. PERFORMING ORGANIZATION NAME AND ADDRESS Naval Postgraduate School Monterey, California 93943		10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS
11. CONTROLLING OFFICE NAME AND ADDRESS Naval Postgraduate School Monterey, California 93943		12. REPORT DATE December 1984
		13. NUMBER OF PAGES 88
14. MONITORING AGENCY NAME & ADDRESS (if different from Controlling Office)		15. SECURITY CLASS. (of this report)
		15a. DECLASSIFICATION DOWNGRADING SCHEDULE

16. DISTRIBUTION STATEMENT (of this Report)

Approved for public release; distribution unlimited.

17. DISTRIBUTION STATEMENT (of the abstract entered in Block 20, if different from Report)

18. SUPPLEMENTARY NOTES

19. KEY WORDS (Continue on reverse side if necessary and identify by block number)

Tropical Cyclone Movement Forecasting

20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

Empirical Orthogonal Function (EOF) analysis is used to represent the environmental wind forcing of selected western North Pacific tropical cyclone tracks from 1979-1983. The EOF analysis is applied separately to the zonal and meridional wind components at 700, 400 and 250 mb on a 527-point grid with 288.7 km zonal and meridional spacing that is relocated with the storm center. The 527 EOF coefficients (for each level and

DD FORM 1473, 1 JAN 73 EDITION OF 1 NOV 65 IS OBSOLETE

S N 0102-LF-014-6601

SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)

20. ABSTRACT Continued

component) are computed for a sample of 682 cases. The coefficient vectors are truncated to the first 35 coefficients based on a Monte Carlo selection criterion. These coefficients account for at least 82 percent of the variance in each field. The EOF coefficients, along with storm movement during the past 24 hours, position, date and intensity, are then used as potential predictors in a regression analysis forecast scheme for tropical cyclone motion. The EOF-based regression equations are tested on the dependent data cases. The mean 72-hour track forecast error is between 450 and 500 km. Therefore, it appears that this regression scheme has potential for operational applications.

Approved for public release; distribution unlimited.

Forecasting of Tropical Cyclone Motion Using an EOF Representation of Wind Forcing

by

William Earle Wilson
Lieutenant, United States Navy
B.S., Presbyterian College, 1975
M.S., Clemson University, 1977

Submitted in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE IN METEOROLOGY AND OCEANOGRAPHY

from the

NAVAL POSTGRADUATE SCHOOL
December 1984

Author: William Earle Wilson
William Earle Wilson

Approved by: Russell L. Elsberry
R. L. Elsberry, Thesis Advisor

Johnny C. L. Chan
J. C. L. Chan, Second Reader

R. J. Renard
R. J. Renard, Chairman,
Department of Meteorology

J. N. Dyer
J. N. Dyer,
Dean of Science and Engineering

ABSTRACT

Empirical Orthogonal Function (EOF) analysis is used to represent the environmental wind forcing of selected western North Pacific tropical cyclone tracks from 1979-1983. The EOF analysis is applied separately to the zonal and meridional wind components at 700, 400 and 250 mb on a 527-point grid with 288.7 km zonal and meridional spacing that is relocated with the storm center. The 527 EOF coefficients (for each level and component) are computed for a sample of 682 cases. The coefficient vectors are truncated to the first 35 coefficients based on a Monte Carlo selection criterion. These coefficients account for at least 82 percent of the variance in each field. The EOF coefficients, along with storm movement during the past 24 hours, position, date and intensity, are then used as potential predictors in a regression analysis forecast scheme for tropical cyclone motion. The EOF-based regression equations are tested on the dependent data cases. The mean 72-hour track forecast error is between 450 and 500 km. Therefore, it appears that this regression scheme has potential for operational applications.

ACKNOWLEDGEMENTS

I would like to express my gratitude to all who have aided me in the preparation of this thesis. Particular thanks go to Drs. R. L. Elsberry and Johnny C. L. Chan who directed my research. In retrospect I thank them for giving guidance when needed and for never making me feel that I was on a time schedule. More importantly, I thank them for their understanding during those weeks that there were no results to show.

Jim Peak is thanked for the times he showed me "the easy way" during data aquisition and analysis. Appreciation is expressed to the Fleet Numerical Oceanography Center, Monterey, California, for providing the Global Band wind data. Kristina Butler and Marilyn Schneider of the William C. Church Computer Center are thanked for their aid in these phases of the research. Many tasks were expedited by their timely assistance. I also gratefully acknowledge the work of CAPT A. R. Shaffer, USAF, whose thesis laid the groundwork for my project.

Two of my preparatory school teachers, Mrs. Tensie Gifford and Mrs. Nellie Merriman, are recognized here not for the facts they taught me but for their inspiration. In particular, Mrs. Gifford is remembered for showing me the beauty of mathematics.

Finally, I dedicate this work to my wife Mary Alice and to the memory of my parents Willard Earle and Hallie Mae Wilson. Always reminding me of the "light at the end of the tunnel", Mary Alice's support and encouragement were there when needed. For the many times she did not complain when I neglected her to be with the computer, I give her my deepest and most heartfelt thanks.

TABLE OF CONTENTS

I. INTRODUCTION 7

A. BACKGROUND 7

B. OBJECTIVES 12

II. DATA ACQUISITION AND FIELD DEFINITION 17

III. EMPIRICAL ORTHOGONAL FUNCTIONS 21

A. BACKGROUND 21

B. THE EOF METHOD 24

C. SELECTING THE NUMBER OF EIGENVECTORS 29

IV. RESULTANT EMPIRICAL ORTHOGONAL FUNCTIONS 32

A. STATISTICAL ANALYSIS 32

B. INTERPRETATION OF RESULTS 34

V. REGRESSION ANALYSIS 38

A. MOTIVATION 38

B. VARIABLE AND CASE SELECTION 39

C. THE EQUATIONS AND ERROR ANALYSIS 42

D. CAUTIONS FOR USE OF THE REGRESSION MODEL . . . 47

VI. POTENTIAL FOR USE WITH INDEPENDENT DATA 49

VII. CONCLUSIONS AND SUGGESTED RESEARCH 53

APPENDIX A: FIGURES 56

APPENDIX B: TABLES 68

BIBLIOGRAPHY 83

INITIAL DISTRIBUTION LIST 87

I. INTRODUCTION

A. BACKGROUND

This study is related to one of the most difficult problems in tropical meteorology--to forecast the movement of tropical cyclones. In discussing the impact of weather on naval forces, materials and operations, Wells (1982) emphasized the role of tropical cyclones. Avoidance of tropical cyclones is important to both military and civilian populations. Fleet operating orders contain lengthy, explicit guidance on tropical cyclone evasion. Yet, serious losses due to tropical cyclones continue to occur. Because of the potential devastation of life and property, continued improvement in the ability to forecast tropical cyclone movement is imperative. The guidance to avoid storm damage is available, but precautions must be taken early. This requires accurate tropical cyclone forecast methodology.

After George and Gray (1976), tropical cyclone movement prediction models can be classified into four categories: (1) steering flow; (2) statistical; (3) numerical; and (4) climatology-persistence. The steering concept treats tropical cyclones as vortices embedded in the basic environmental flow. The statistical forecast approach commonly uses a screening procedure to select meteorological variables that are correlated with tropical cyclone movement. These variables are then used to develop regression equations for prediction. An analog-statistical model is based upon the assumption that historical families of repetitive storm tracks are associated with repetitive synoptic patterns. By scanning historical data records, a computer algorithm is used to associate an existing storm with a

"parent" storm track or with a family of similar storms. The numerical method involves predictions of the synoptic flow surrounding a cyclone, and possibly a simulation of cyclone structure, to predict storm movement. Prediction of tropical cyclone movement based on climatology and/or persistence is based upon empirical relationships derived from historical records of the tracks of previous cyclones. Objective methods for forecasting tropical cyclone movement have been developed using one or more of these prediction models. As yet, no one of these objective techniques has been found to be superior to the others under all conditions (e. g., Neumann and Pelissier, 1981).

The simplest numerical method of predicting tropical cyclone movement is to use a barotropic model on a relatively coarse grid (Sanders and Burpee, 1968) with a point vortex advection scheme (Renard, 1968). Results obtained from these methods demonstrated that there is considerable information in the analyzed and predicted synoptic fields represented on grids which lack the fine resolution necessary to resolve the intense wind field near the center of a tropical cyclone. However, Ley and Elsberry (1976) cited these models as inadequate due to the lack of a unique steering level (or layer) and the absence of vortex-environmental interaction. Still, the relative success of coarse-mesh models supports the idea that it might be possible to relate large-scale forcing (by advective processes) of a tropical cyclone to its subsequent movement.

Current statistical models for the prediction of tropical cyclone movement use predictors derived from climatology, persistence and either observed or numerically forecast geopotential height data (such as gradients, thicknesses and time changes). For example, Neumann and Randrianarison (1976) developed a purely statistical model based on a system of regression equations for the prediction

of tropical cyclone movement over the Southwest Indian Ocean. Basically, the model is CLImatology plus PERsistence (CLIPER), applied to the Indian Ocean. Stepwise regression was used to develop second-order polynomials (35 variables) to predict the zonal and meridional cyclone displacements. The resultant model's performance compared favorably with operational models (Joint Typhoon Warning Center, 1983). A significant number of North Atlantic tropical cyclones exhibit anomalous motion characteristics (Neumann, 1981). The forecast tracks of these storms revealed limitations of purely statistical forecast systems (Neumann and Lawrence, 1975). While some researchers sought to develop purely dynamical models (e. g., Miller et al., 1972), others developed statistical-dynamical models. The current NHC statistical-dynamical model, NHC73, was described by Neumann and Lawrence (1975). The results demonstrated that information obtained from numerical prognoses can improve the performance of statistical tropical cyclone prediction models.

Statistical models for the prediction of tropical cyclone movement have traditionally used a coordinate system oriented with respect to the zonal and meridional axes. Tropical cyclones tend to move with the synoptic flow. Short-term displacements have a very strong persistence component. For these reasons, a grid system oriented with respect to the cyclone's heading would be a natural choice. Shapiro and Neumann (1984) investigated the error-reducing potential of a grid system oriented with respect to the cyclone heading. This grid-reorientation technique resulted in a 40 percent reduction of the total variance of tropical cyclone movement. It was shown, using the dependent data sample, that a potential reduction of 24-hour forecast errors by approximately 13 percent could be realized for synoptic predictors extracted on a rotated grid. This

reduction in error was comparable to the reduction in 24-hour forecast errors during the past 25 years (Shapiro and Neumann, 1984). It was observed that the entire reduction of forecast error is not realizable due to random and real errors in the developmental and operational height data, respectively. Satisfactory results were not obtained using rotated grids for prediction of 48- and 72-hour tropical cyclone movements. An analysis of forecast results revealed that grid rotation optimized forecasts in the direction along which the variance of tropical cyclone movement is maximized and tended to orient the displacement vectors with the along-track direction. The results of Shapiro and Neumann (1984) indicated the potential forecast improvement that can be made in short-term forecasts with current synoptic data if the cyclone's heading is known. However, these concepts must still be tested in an operational environment. For this reason, the data grid used in this study was geographically oriented. This grid system will be described in the next chapter.

Both statistical and dynamical methods have weaknesses (Haltiner and Williams, 1980; Shaffer, 1982). Statistical methods usually do not forecast well those cyclones that have anomalous motions. This problem relates to the "scope" of a model, as discussed in Chapter V. Similarly, these methods are typically not robust against small changes in the synoptic (dynamic) forcing of a cyclone. There is a general tendency of statistical methods toward homogenized, or smoothed, forecasts. In comparison, dynamical models suffer from both theoretical and financial limitations. Due to the smallness of the Coriolis parameter in tropical regions, geostrophy cannot be assumed and initialization of data fields is difficult. Erroneous data used to initialize a model can rapidly deteriorate a numerical forecast. Convective heating is one of the primary driving mechanisms

for the maintenance of a tropical cyclone. The difficulty of modeling convective heating, together with initialization problems, makes dynamical model predictions suspect in the tropics. More importantly, maintenance of the energy balance for a tropical cyclone requires an interaction among different scales of motion (Coyama, 1982). To avoid spurious solutions, a small grid mesh is necessary for a dynamical model to numerically simulate these interactions. Furthermore, the expense of numerical integration on a fine mesh can be quite large due to the Courant-Fredrichs-Levy (CFL) condition, which requires integration to be made with smaller time steps as the mesh is decreased (Haltiner and Williams, 1980). An additional difficulty encountered with a fine-mesh model is that observed data in tropical regions are inadequate for model initialization.

Neumann and Pelissier (1981) studied the performance characteristics of various tropical cyclone movement prediction models in operational use at the National Hurricane Center (NHC) in Miami, Florida. These models are representative of the current methodology for prediction of tropical cyclone movement. The seven models range in complexity from the basic analog to the sophisticated numerical and are identified in Table I as statistical, statistical-synoptic, statistical-dynamical or dynamical. Four of the statistical schemes are regression-equation models. Predictors for these equations are generally derived from climatology, persistence and geopotential height data (except CLIPER). A fifth statistical model (HURRAN) uses an analog approach. Operational analysis of CLIPER and HURRAN (Hope and Neumann, 1970) showed that each of these models gives almost identical forecast tracks.

For forecasting western North Pacific tropical cyclones, five main categories of objective techniques are used by the Joint Typhoon Warning Center (JTWC), Guam, Marianas Islands:

where $a(i,j)$ is the corresponding element of matrix A, and $b(i)$ and $s(i)$ are respectively the mean and standard deviation of the elements in row i of matrix A (that is, the mean and standard deviation at a particular point of the equidistant grid computed over all cases.) The elements of Z are dimensionless variates of zero mean and standard deviation one. The main advantage of using standardized data is that it effectively treats the systematic variation in magnitude of the elements of the data matrix A. This is beneficial for the reasons given in Chapter II. The same systematic error can occur with the use of the covariance matrix, which also introduces the need for dimensional scaling to return to the form of the input data prior to interpretation of the eigenvectors. A disadvantage of using the correlation matrix is potential, but slight, smoothing of the results (Kutzbach, 1967).

The correlation matrix (R) then is the symmetric matrix:

$$R = ZZ'/n \quad , \tag{3.2}$$

where n is the number of cases, and a prime is used to denote the transpose of a matrix or vector. Next, it is necessary to determine the following constrained maximum:

$$\text{Max } \{y\colon e'e = 1\} \text{ where } y = e'Re \tag{3.3}$$

for the m dimensional column vector e. The scalar y is the correlation between vector e and the data matrix A. The constraint requires that the vector e be normalized to length one. Morrison (1967) applies the method of Lagrange multipliers to (3.3) to obtain:

$$(R - vI) e = o \quad , \tag{3.4}$$

Pacific wind vectors. The complex EOF results linked the spatial and temporal patterns of the data fields. This fusion of space-time variations is particularly useful for long-term records over large spatial areas. The temporal variance of the data was partitioned into orthogonal spatial patterns (the eigenvectors). The complex coefficients computed were shown to be a time series modulating the eigenvectors which were associated with physical patterns (signals) that accounted for a large percentage of the total variance. Legler further demonstrated that it is possible to obtain statistical information that could not be obtained using a scalar analysis of the wind components.

Whether to perform a scalar or a vector EOF analysis is a fundamental consideration. Kjelass (1971) has edited several articles on the theory and methodology of scalar and vector EOF analysis. These articles include illustrative examples of the application of the methodology in geophysics. For vector data, a more realistic representation would be expected from a vector EOF analysis, as demonstrated by Legler (1983). However, it would be rash to assume that a vector analysis is necessarily best for vector data. As discussed in Chapter IV, the meridional and zonal wind components comprising the data for this study were subjected to a scalar EOF analysis. The mathematical procedure for this analysis is described in the next section.

B. THE EOF METHOD

Let A be an m x n matrix containing n cases of m-variate data. The following development will be for the scalar EOF analysis of the standardized data matrix Z with elements z(i,j) defined by:

$$z(i,j) = [\ a(i,j) - b(i)\ ] \,/\, s(i) \quad , \tag{3.1}$$

meteorological forcing patterns. Because of their inherent empirical nature, it is not required, and hence not always found to be the case, that the eigenvectors have a physical interpretation that accounts for any variation of the field being analyzed.

Application of the EOF methodology to wind data has been done in various manners. For example, Barnett (1977) applied an EOF analysis to Pacific trade wind data separated into zonal and meridional components. The result was an analysis of two separate scalar fields. Alternately, the treatment of the wind as complex numbers for the EOF technique was presented by Hardy (1977). Hardy and Walton (1978) analyzed mesoscale wind vector measurements at ten stations in the San Francisco Bay Area. This report included a useful mathematical appendix describing the analysis of complex (that is, vector) data, since EOF analysis of two-dimensional vector data is achieved by use of complex rather than real numbers. This extension of the methodology is straightforward. The time series analysis of the temporal component patterns was also illustrated. Results of this study confirm that EOF analysis can be advantageously applied to large sets of regional wind velocity data. The method objectively derived the essential spatial and temporal properties represented by the data, and enabled a quantitative development of "prototype" cases and a quantitative comparison of regional velocity patterns on a month-to-month basis. This is similar to the application of EOF analysis for map typing. For example, Brown (1981) used EOF methods to divide height fields surrounding tropical cyclones into smaller classes based on the derived coefficients. These classes were used for an analog scheme to forecast tropical storm movement.

Legler (1983) applied the method of Hardy and Walton (1978) to 18 years of monthly-average records of tropical

expansion coefficients are a time series representation of these temporal patterns (Hardy and Walton, 1978; Legler, 1983).

Examples of the use of eigenvectors (eigenmodes) in meteorological applications include those of Lorenz (1956) in statistical weather prediction, Grimmer (1963) in an analysis of temperature patterns in Europe, and Mateer (1965) in an analysis of observations of ozone distribution from sky-light intensities. Many other studies can be found in the meteorological literature. Hardy and Walton (1978) gave a broad survey of possible applications of the analysis of scalar data. The mathematical details of the scalar EOF method are described in the next section.

There are particular advantages afforded by an EOF data analysis. It is not necessary for the data to be stationary (in a statistical sense), nor do they have to be uniformly sampled in space or time. The EOF method is a convenient, cost-effective and objective means to represent large amounts of synoptic data by comparatively few coefficients. While numerical storage is not normally a problem with modern computers, it is important that the researcher be able to represent synoptic fields in a "compact" manner. Also, these coefficients can be readily incorporated into a regression analysis. Kutzbach (1967) gives a particularly clear description of an EOF analysis that was used to reduce 23 temperature observations at 25 grid points to five eigenvectors which accounted for 88 percent of the total variation. Similarly, Stidd (1967) performed an EOF study of the average monthly rainfall in Nevada and was able to account for 93 percent of the total variance using only three eigenvectors and coefficients. The eigenvectors were successfully associated with factors related to rainfall. These examples demonstrate the effective use of EOF analysis for data reduction and for possible identification of

III. EMPIRICAL ORTHOGONAL FUNCTIONS

A. BACKGROUND

The general application of eigenvectors in an EOF analysis is similar to the representation of a field in terms of orthogonal functions. While orthogonal functions are generally simple functions such as sines and cosines, eigenvectors are derived from the data fields. After suitable ranking, a few eigenvectors may represent a significantly higher proportion of data variance than would the same number of orthogonal functions. The statistical methods known as principal component analysis and empirical orthogonal function analysis (also referred to as empirical eigenvector analysis) are in essence the same. The principal components are the same coefficients that would be derived from an EOF analysis.

The EOF analysis is an objective, mathematical procedure which starts with either the correlation or covariance matrix of the original data matrix. From the cross-product matrix, the eigenvalues and eigenvectors are derived. The normalized eigenvectors form a complete orthonormal basis of vectors which can be used to represent the original observations. It will be shown that the relative magnitudes of the eigenvalues can be used to rank-order the eigenvectors (modes) in terms of their significance in representing the data. Furthermore, the most significant eigenvectors (that is, those which represent the greatest percentage of variability in the data) can often be identified with physically important patterns in the original data. While not important for this study, it is noted that data containing recurrent temporal variations have spatial eigenvectors whose

tropical cyclone maintenance (Gray, 1979). The vertical shear of the mean zonal wind near the cyclone center is not large and changes sign across the center. The shear is positive to the poleward side and negative to the equatorward side of the cyclone. Also, the line of zero zonal vertical shear crosses near the cyclone center.

These mean wind fields thus show that the GBA are capable of representing the flow around tropical cyclones. In the next chapter, the method of using EOFs to represent this flow for all the cases in the sample will be described.

are shown in Figs. 1-6. The means and standard deviations were based on all 682 cases. As shown in Figs. 1-6, the variability of the winds is largest in the northeast quadrant of the equidistant grid at all three levels. Because the variability of wind speed is not uniform throughout the grid, standardization of the winds by the mean and standard deviation at each grid point is essential to ensure that regions of the grid where variability is generally higher do not "dominate" in an EOF analysis. The standardization of data will be presented Chapter III.

The mean zonal and meridional flow patterns at 700 mb appear to be physically reasonable. The mean zonal flow in Fig. 1 shows easterlies (westerlies) to the north (south) of the storm center. Although the grid resolution does not reveal the fine structure of the storm, the cyclonic environment of the storm is evident. The mean meridional wind component in Fig. 2 is dominated by southerly (northerly) flow to the east (west) of the storm. Again, the cyclonic shear envelope of the storm can be clearly identified. The mean zonal wind fields (Figs. 1, 3 and 5) show significant strengthening of the westerlies north of the storm from 700 mb to 250 mb. The strong, positive meridional flow northeast of the storm at 400 mb and 250 mb (Figs. 4 and 6) could be an indication of a possible outflow channel, which has been shown to be favorable for tropical cyclone intensification (Chen and Gray, 1984).

The low-level cyclonic and upper-level anticyclonic circulations in the mean wind fields are generally representative of mostly mature cyclones. It is recognized that computation of the mean fields was not restricted to cases for which the developing cyclone had matured to tropical storm intensity or to cases of intensifying cyclones. Nevertheless, Figs. 1, 3 and 5 indicate patterns of the vertical shear of zonal wind that have been associated with

intensity (maximum sustained winds of 18 m/s (35 kts) or greater) must have been present west of the dateline. The JTWC warning position at the times the GBA were produced must have been at a latitude less than 34.6 N to ensure that data were available for a sufficient latitudinal extent north of the cyclone center. Finally, the GBA must be available for the zonal and meridional wind components at 700 mb, 400 mb and 250 mb.

A total of 1357 cases were found to meet the above criteria. Because of computation-time limitations subsequently encountered, the initial data set was later reduced to 682 cases by random selection. These 682 cases comprised the data set from which the EOF functions were computed. However, all 682 cases were not suitable for the regression analysis due to an inadequate history or future storm record. The selection of cases for the regression analysis will be described in Chapter V.

A relocatable 527-point grid was defined with a fixed zonal and meridional separation of 277.8 km (150 n mi). The grid in Fig. 1 is typical. There are 31 grid points west to east and 17 south to north. The horizontal resolution is twice that of Shaffer (1982), with about 4 1/3 times the number of grid points (527 vice 120). The equidistant grid extends 8334 km (4500 n mi) zonally and 4445 km (2400 n mi) meridionally. The grid is moved for each case so that the tropical cyclone center is always located at the (0,0) grid point. For each case, the zonal and meridional wind speeds at 700 mb, 400 mb and 250 mb were were extracted from the GBA onto the equidistant grid using a bilinear interpolation method (on a spherical Earth). The warning position from the JTWC was used to locate the cyclone center.

Contours of the mean and standard deviation fields of the zonal and meridional winds at 700 mb, 400 mb and 250 mb

II. DATA ACQUISITION AND FIELD DEFINITION

Wind data used in the present study are from the Global Band Analyses (GBA), which are operationally generated by the United States Navy Fleet Numerical Oceanography Center (FNOC). The GBA are produced on a 49 x 144 Mercator grid. At 22.5 N or S, the grid mesh distance is 257 km. The GBA provide complete longitudinal coverage over latitudes 40.956 S to 59.745 N. Grid points are always separated by 2.5 degrees of longitude. However, convergence of the meridians causes the actual zonal distance separating grid points to decrease toward higher latitudes. Along the northern boundary of the GBA grid from 58.462 N to 59.745 N, the longitudinal separation of the grid points undergoes a 3.7 percent decrease. This should not be an important source of error given the inherent uncertainties of the raw data. The GBA were available for the period 0000 GMT 5 January 1975 to 1200 GMT 31 December 1983. Data were available at 0000 GMT and 1200 GMT for the zonal and meridional wind components at the following levels: surface, 700 mb, 400 mb, 250 mb and 200 mb. It is noted that the GBA are missing for some dates and times at one or more levels.

Data for western North Pacific tropical cyclones are available from the annual tropical cyclone reports of the JTWC. At six-hour intervals, warning position, best track position, estimated intensity (maximum sustained wind speed and minimum surface pressure) are given, as well as forecasts for 24, 48 and 72 hours. The JTWC annual reports for the years 1979 to 1983 were used to select the cases used in this study. To apply the technique proposed in Chapter I, the following conditions for case selection were imposed. A tropical cyclone which matured to at least tropical storm

are determined by regression equations for the orthogonal components of motion. Chapter VI addresses the important question of applicability of the model for independent data. The concluding Chapter VII contains suggestions for further research.

an EOF-based regression approach can provide a simple, low-cost technique for prediction of tropical cyclone motion.

The extent to which the surrounding flow can be used to predict tropical cyclone movement has been explored by studies such as Shaffer and Elsberry (1982) and is a key motive for this study. The motion of a tropical cyclone is not determined solely by forces acting on one pressure level but rather by the mean wind flow integrated through a deep layer and over a substantial area surrounding the cyclone (Miller and Moore, 1960). Because a single steering level has not been established, these regression studies involve a single-level model that is tested with predictors extracted on three different levels. The primary purpose of the current study is to use analyzed wind fields to represent synoptic forcing in a tropical cyclone movement forecast technique. Both Shapiro and Neumann (1984) and Shaffer and Elsberry (1982) worked with geopotential height data. Because the wind fields are generally more representative of the flow in the tropics, it is hypothesized that a study similar to Shaffer's using wind data could result in further improvement of forecast ability.

The techniques that have been applied are not new. The uniqueness of the new forecast scheme is the use of an EOF representation of the wind forcing in the prediction of tropical cyclone movement. This forecast method can be described as a statistical-climatological tropical cyclone forecast method which uses an EOF representation of the synoptic-scale wind forcing.

Chapter II discusses the acquisition of data and the grid system used. The EOF methodology and analysis are described in Chapters III and IV. In Chapter V, the resultant equations from a regression analysis are used to develop a prototype forecast scheme. Future storm positions

the synoptic-scale features adjacent to the tropical cyclone. One approach is to consider the cyclone to be a point vortex whose direction and speed are approximated by the direction and speed of the surrounding winds (or, equivalently, the pressure or height gradients across the cyclone). The steering level is that pressure level at which the wind speed and direction best correlate with those of the cyclone. The steering level theory has been applied in several tropical cyclone movement forecast schemes; for example, Riehl and Shafer (1944), Miller and Moore (1960), Tse (1966) and Renard <u>et al</u>. (1973). Different steering levels are used by the various forecast schemes. However, the general concensus is that the mid-tropospheric levels (700 mb and 500 mb) are the best for predicting tropical cyclone movement (Chan and Gray, 1982). The upper tropospheric level winds have not been found to be useful for tropical cyclone movement prediction (Jordan, 1952; Miller, 1958).

Statistical regression equations were developed by Shaffer (1982) to predict the zonal and meridional displacements of tropical cyclones at 12-hour intervals to 84 hours. Eof coefficients of the dependent sample were used to represent the synoptic forcing in the equations. Forecast errors were competetive with other statistical methods. The average vector displacement error for an independent sample was approximately 17 percent smaller than the long-term average official JTWC forecasts. The best overall forecasts were obtained using equations derived with 500 mb height data. For these equations, the vector displacement forecast errors obtained for the independent sample were 164 km (88 n mi), 333 km (176 n mi) and 513 km (277 n mi) for 24-, 48- and 72-hour forecasts, respectively. It is noted that a shortcoming of Shaffer (1982) was the smallness of the independent sample, but the study demonstrated that

number of grid-point predictors would be prohibitive. The difficulties inherent in both statistical and dynamical methods motivated Shaffer (1982) and Shaffer and Elsberry (1982) to develop a statistical-climatological tropical cyclone track prediction technique using an EOF representation of the synoptic forcing. The EOFs provided an alternative to grid-point predictors. The technique enabled the representation of fields of 120 grid points by 10 eigenvectors and their associated EOF coefficients. Eighty-five percent of the total variance of the data was accounted for by these 10 modes. Shapiro and Neumann (1984) also used 10 modes to account for 98 percent of the total variance in geopotential height data in either a rotated or geographically-oriented grid system. These advantages of data reduction and simple numerical representation of synoptic fields make the EOF technique ideal to use with regression analysis. The eigenvectors represented different patterns relating to tropical cyclone movement; that is, patterns which appeared to be physically important in the determination of tropical cyclone movement. This approach was novel for forecasting of storm movement in the sense that previous regression analysis methods (e. g., Neumann and Lawrence, 1973) had not incorporated the entire synoptic forcing field.

That the synoptic flow surrounding a tropical cyclone is a major determinant of cyclone movement has been long observed (Chan and Gray, 1982). In particular, it has been well established that tropical cyclone movement is significantly related to mid-tropospheric surrounding wind patterns (Chan *et al*., 1980). Neumann and Lawrence (1975) associated most of the variance reduction by statistical models for prediction of tropical cyclone movement with input from three sources: (1) climatology and/or persistence; (2) some type of "steering"; and (3) the position and intensity of

(1) climatological and analog techniques; (2) extrapolation; (3) steering techniques; (4) dynamic models; and (5) empirical and analytical techniques. A brief description of the objective techniques used is given in the annual report (Joint Typhoon Warning Center, 1983). In contrast to the NHC, the JTWC has not placed emphasis on the development of statistical methods. The variety and range of sophistication of techniques in operational use at the NHC and the JTWC for objective forecasting of tropical cyclone movement is noteworthy. That simple methods such as mere extrapolation are competetive with complicated numerical models might be taken as a surprising indication that little progress has been made in the improvement of forecast skill. Alternately, the indication could be that tropical cyclones are not predictable solely by use of a single class of methods. For the years 1972-1983, the magnitude of the track forecast error by the JTWC for western North Pacific tropical cyclones was approximately 213 km (115 n mi), 407 km (220 n mi) and 667 km (360 n mi) for the 24-, 48- and 72-hour, respectively (Joint Typhoon Warning Center, 1983). Improvement over these forecast errors is seen to be a realistic goal.

B. OBJECTIVES

The main objective of this study is to develop a "statistical-climatolcgical" method to forecast tropical cyclone movement. However, computational requirements for the development of a regression model from a large synoptic grid system limits the number of possible grid-point predictors. An Empirical Orthogonal Function (EOF) approach similar to that used by Shaffer and Elsberry (1982) is therefore adopted. If an attempt were made to develop a regression model using a large synoptic grid system, the

where v is the Lagrange multiplier, I the identity matrix and o the null vector. Nontrivial solution of (3.4) requires v to satisfy:

$$|R - vI| = 0 \quad . \tag{3.5}$$

The values of v are thus the eigenvalues of the correlation matrix R, and e is the associated (normalized) eigenvector. Premultiplication of (3.4) by e' and application of the constraint e'e = 1 from (3.3) gives:

$$v = e'Re \quad . \tag{3.6}$$

Since v was chosen to maximize this correlation, v must be the largest eigenvalue of R. Morrison (1967) extends this constrained maximum method to show that the m eigenvalues of R account for the variance in each of the m dimensions. In the following discussion, the eigenvalues are ordered such that:

$$v_1 > v_2 > \ldots > v_m \quad . \tag{3.7}$$

Also, the importance of the ith eigenvalue is measured by

$$L_k = \sum_{i=1}^{k} v_i \Big/ \sum_{j=1}^{m} v_j = \sum_{i=1}^{k} v_i \Big/ \mathrm{tr}R \quad , \tag{3.8}$$

where L_k is the fraction of the total variation in R accounted for by the eigenvectors associated with the k largest eigenvalues. The trace of the correlation matrix (tr R) is equal to its order (m).

Any of the input data cases (stored in a particular column of A) is "reproduceable" by application of the EOF coefficients defined by:

$$C = E'A \quad , \tag{3.9}$$

where C is an $m \times n$ orthogonal matrix and E is the $m \times n$ orthonormal matrix of the eigenvectors. Matrix E is formed such that column j holds the normalized eigenvector associated with eigenvalue j. Since E is orthonormal, (3.9) gives directly that the data matrix A can be recreated as:

$$A = EC \quad . \tag{3.10}$$

Thus, The EOF analysis results in a factorization (3.10) of the data matrix A. Matrix E of eigenvectors represents the <u>spatial</u> decomposition of the data variance into orthogonal modes. The coefficient matrix C accounts for the <u>temporal</u> variance.

The replication of the data matrix A is exact. The potential for application of the analysis with independent data is discussed in Chapter IV. It is noted that exact reproduction is not possible for cases not in the developmental set of cases. Such a recreation would not be possible using a finite sum of functions of an orthogonal family. Case j (stored in column j of matrix A) is represented by a linear combination of the orthogonal coefficients and eigenvectors:

$$a(j) = \sum_{i=1}^{m} c(i,j) \bullet e(i) \quad \text{for } j = 1, \ldots, n \quad , \tag{3.11}$$

where a(j) is the column vector j of matrix A, the c(i,j) are elements of the coefficient matrix C and e(i) is the eigenvector in column i of matrix E.

A word of caution should be given here. The factorization (3.10) is unique up to the coefficient signs since the coefficients are computed such that the variance is partitioned orthogonally into successively smaller portions.

This uniqueness results since the partitions formed are distinct. The researcher might be tempted to use orthogonal (matrix) transformations on the coefficient matrix in an attempt to simplify the interpretation of the subject matter. The transformed matrix will generate the original data just as exactly as before; however, the eigenvectors no longer represent the same maximum percentages of variance.

It is generally found that an adequately large percentage of the total variation in R (and hence in A) can be attributed to the first p eigenvectors such that p is much smaller than the total number of eigenvectors (m), particularly when m is large (Morrison, 1967). Case j is then approximated by:

$$a(j) = \sum_{i=1}^{p} c(i,j) \cdot e(i) \quad \text{for } j = 1, \ldots, n . \tag{3.12}$$

It is possible to recreate the input data elements of matrix A from the standardized matrix Z. If the first p eigenvectors are retained, then (3.11) is approximated by:

$$a(i,j) = \sum_{k=1}^{p} [\ c(k,j) \cdot e(i,k)\ ]\ s(i) + b(i) \quad , \tag{3.13}$$

where the $e(i,k)$ are elements of the eigenvector matrix E.

Shaffer (1982) discussed the rotation of eigenvectors computed in an EOF analysis. He gave a very simple example of rotation and contrasted orthogonal rotation with oblique. The possibility that unrotated eigenvectors may not represent the true synoptic patterns was also explored and evidence given that this should not occur for true geophysical synoptic fields. Rotation was not performed on the eigenvectors in this study for several reasons. First, the eigenvectors were needed to generate the coefficients to be used for the regression analysis. As such, the ability to interpret physically the eigenvectors is not as important

as in studies in which this is a major objective. For example, Legler's (1983) study of the tropical Pacific trades showed that rotation of the resultant eigenvectors can be essential to interpreting the patterns as well as to simplifying the statistical analysis of the data. Second, a goal of this study was to reduce the data required for forecasting. This was done by analyzing the amount of variance accounted for by the various eigenvectors. Were the eigenvectors to have been rotated, they would no longer account for the same percentage of the total variance. For further discussion on the rotation of eigenvectors, the reader is referred to Richman (1981).

C. SELECTING THE NUMBER OF EIGENVECTORS

One important advantage of the EOF technique is that of summarizing most of the variation in a multivariate system in terms of fewer variables. Unless the system is defective (less than full rank), some variance will always be unexplained if fewer than m, the row dimension of the data matrix A, are taken to describe the system. The problem faced by the model builder is to determine the number of eigenvectors to provide a parsimonious, yet fairly adequate, description of a data system. Various methods have been applied to determine how many eigenvectors are significant; that is, possess maximum information with minimum noise. The classical methodology outlined by Morrison (1967) is based upon the asymptotic behavior of the eigenvalues. This approach operates on the assumption of a large sample of normal data. If standardized data are utilized, the sampling statistics are considerably more complex (Anderson, 1963). Preisendorfer and Barnett (1977) observed that this method is generally not suited to geophysical studies in which sample sizes are too small to have the requisite

asymptotic behavior. Shaffer (1982) found the asymptotic assumption to be invalid for his study of 504 cases (with 120 data points each) of geopotential heights. Another alternative is to use the LEV (Logarithmic EigenValue) diagram method (Rinne and Karhila, 1979) which identifies those structural differences of the eigenvectors that describe noise instead of signal. Although this method is simple, it is unsatisfactory because of the subjectivity required on the part of the researcher and the lack of a strong theoretical basis. Other methods such as those of Richman (1980) or Brown (1981) are also rejected because they are too subjective in their applications. Methods such as presented by Cattell (1958) and Guttman (1954) are considered unsuitable because of the danger of probable overfactoring and their lack of a scientific basis.

The method used in this study is a Monte Carlo approach (Preisendorfer and Barnett, 1977). This approach was chosen over Morrison's (1967) because: (1) it does not require asymptotic behavior of the eigenvalues; (2) it is objective; and (3) it is based on statistical methodology. The first step in this method is to generate at random a large number (at least 100) of data fields consisting of standard normal deviates, which are then assembled into a matrix Z. Matrix Z is therefore assumed to represent a data matrix obtainable if all processes are purely random. Next, the eigenvalues are computed for each matrix Z. Means and standard deviations are determined for the simulated eigenvalues. The eigenvalues obtained from the physical data are compared with those from the simulated deviates. If the true eigenvalue deviates from the mean of the corresponding random data eigenvalues by more than two (three) standard deviations, then the true eigenvalue is significant at the 95 percent (98 percent) confidence level (Preisendorfer and Barnett, 1977). That is, deviation of the true eigenvalue

from the mean simulated eigenvalue by at least two standard deviations is indicative that the associated eigenvector represents signal rather than noise. As successive coefficients are computed, a running sum (using (3.12) or (3.13) as appropriate) can be formed and compared with data matrix A to determine how well the data matrix is being generated by a smaller number of modes.

IV. RESULTANT EMPIRICAL ORTHOGONAL FUNCTIONS

A. STATISTICAL ANALYSIS

The mathematical and theoretical framework developed in Chapter III was used for a scalar EOF analysis of the dependent data set (682 cases as described in Chapter II). The major purpose of this phase of the data analysis was to compute the EOF coefficients needed for the tropical cyclone motion forecast scheme proposed in Chapter I. Since these EOF coefficients were needed for use as possible predictors in separate regression equations for zonal and meridional storm movement, a scalar rather than vector representation was considered to be adequate. For each of the zonal and meridional wind fields at 700 mb, 400 mb and 250 mb, a 527 x 682 data matrix A was formed using the interpolated fields as columns. A matrix Z of standardized data was computed for each matrix A, and the resultant eigenvalues and corresponding eigenvectors were determined. For each wind-component field, 527 modes (eigenvectors) were generated. The EOF coefficients for each of the 682 cases were also computed for each of the six wind-component fields.

The eigenvalues and cumulative percentage of total variance for the zonal and meridional fields are presented by pressure level in Tables II through IV. The eigenvalues, and hence the significance of their associated modes, decrease rapidly with increasing mode number. Zonal-field eigenvalues decrease at approximately twice the rate of decrease of the meridional eigenvalues.

Although many modes resulted because of the number of grid points per case, most of the higher order modes represent noise rather than signal. To determine the number of

modes to be retained, a Monte Carlo simulation was run as described in Chapter III. A random number generator for standard normal deviates was used to simulate 100 standardized 527 x 682 data matrices Z. The statistical "structure" of these random fields parallels that of the standardized fields of the real data. For each of the 100 simulated matrices of 682 cases of random standard scores, the EOF analysis was performed to yield 100 sets of 527 eigenvalues (one per field grid point). The means and standard deviations of the Monte Carlo eigenvalues were computed. If the eigenvalue for a mode computed from the real data was greater than the corresponding mean eigenvalue plus twice its standard deviation as computed from the random data, then the eigenvalue and eigenvector from the real data were selected as representing atmospheric signal. The corresponding mode was retained at the 95 percent confidence level. Table V contains the mean eigenvalues of the Monte Carlo simulation as well as these mean eigenvalues plus twice their standard deviation.

Comparisons of the six sets of real-field eigenvalues to those of the random fields are performed separately since the number of significant eigenvectors may be different for each level. The only relationship between the modes of the six fields for the three levels comes from any vertical coupling that may exist. Fig. 7 illustrates the eigenvalues for the 700 mb zonal wind field and the Monte Carlo simulation for the first 40 modes. Twenty-four modes are indicated to represent signal. Table VI is a summary of the number of modes to be retained and the percentages of total variance described according to the Monte Carlo selection criterion. Some general observations can be made. For either the zonal or the meridional flow, the number of modes that represent signal at 700 mb is less than that at 400 mb, which in turn is less than that at 250 mb. For any of the

levels analyzed, a smaller number of zonal modes than meridional are retained with a higher percentage of total variance represented.

B. INTERPRETATION OF RESULTS

The percentages of variance unexplained (noise) is realistic for a tropical wind analysis. Errors are largely due to data distributions or measurement errors. The analysis problem is difficult because of the weak governing mass-wind balance relationship in the tropics (Haltiner and Williams, 1980). Therefore, it is plausible that the level of random error in the wind-component fields is as high as 18.3 percent. This maximum percentage of "noise" (for the meridional wind fields at 700 mb) corresponds to the largest number of modes (35) selected to represent "signal".

In the subsequent regression analysis, only the first 35 modes of the zonal and meridional wind fields will be used in the development of the corresponding zonal and meridional storm movement equations for each of the three pressure levels analyzed. The retention of 35 modes for each wind component field provided the maximum possible selection of modes without including unnecessary noise. Using only 35 coefficients out of 527 is a remarkable data reduction of 93 percent. For each field it is necessary to store only the eigenvector matrix E and the first 35 coefficients for each case, which will account for no less than 81.7 percent of the total variance. Table VII lists the percentages of variance accounted for when 35 modes are retained for all wind component fields. At least 90 percent of the total variance of any zonal wind field is accounted for. While the number of EOF coefficients needed is much larger than the 10 per case in Shaffer (1982), 35 modes per field is still a tractable number of potential predictors for regression analysis.

It is beneficial to investigate the physical significance of the modes determined to represent signal. Shaffer (1982) found that the broad-scale features of eigenvectors derived from geopotential height fields had meteorological meaning. Contours of modes one and two (multiplied by 100) for the 700 mb zonal and meridional fields are presented in Figs. 8 and 9. The eigenvectors are non-dimensional, since standardized data were used for the EOF analysis. Two points must be stressed. First, there is no mathematical connection between any zonal-field mode and the same mode of the meridional field. That is, it is not possible to regain the vector nature of the wind by a combination of zonal and meridional eigenvectors. Second, each eigenvector represents the pattern shown as well as the <u>exact</u> inverse of the pattern. For a given field, the forcing pattern of a particular eigenvector is dependent upon the sign of the associated EOF coefficient. If the coefficient is negative, then the forcing pattern of the eigenvector is "inverted". Positive (negative) components of the field are reversed to negative (positive). The following discussion will use eigenvector patterns as shown without considering the inverse patterns.

The patterns of the 700 mb modes 1 and 2 in Figs. 8 and 9 can be interpreted separately as possible atmospheric flow patterns. Mode 1 of the 700 mb zonal flow (Fig. 8) shows a cyclonic shear across the cylone, with easterlies to the north of the cyclone and westerlies to the south. Mode 2 of the 700 mb zonal flow (Fig.8) is dominated by broad easterly flow. The zonal modes 1 and 2 at 400 mb and 250 mb (not shown) are characterized by diminished equatorial westerlies to the south of the cyclone. Modes 1 and 2 of the 700 mb meridional flow (Fig. 9) both show alternating bands of positive and negative flow. These patterns are typical for trough-ridge-trough arrangements. Speed maxima

in the bands are located north of the cyclone. The cyclone is again located in a region of cyclonic shear. Meridional modes 1 and 2 at 400 mb and 250 mb (not shown) depict the eastward slope of the 700 mb patterns with elevation. These modes, which individually account for the largest percentages of total variance in their corresponding fields, are indeed patterns or signals that appear to relate to tropical cyclone movement.

Complexity of the eigenvectors made it difficult to associate observable atmospheric patterns with higher order modes for any of the fields. Legler (1983) has observed that examination of the eigenvectors to give appropriate physical interpretations may be impractical for data collected over large grids. Over large areas, signals from two or more physical processes may be overlaid in a single eigenvector. This can occur since there are no restrictions as to how the patterns for a particular process may be "decomposed" among the eigenvectors. Moreover, particularly strong atmospheric signals may appear in more than one eigenvector. Under such circumstances any realistic interpretation of the modes may be precluded.

It is also important to verify that the significant modes selected for retention do satisfactorily represent the data fields. A case (0000 GMT 30 July 79) was selected at random to demonstrate the reconstruction capability of an EOF analysis. At this time, Typhoon Hope was at approximately 16.9 N, 133.4 E with maximum sustained winds of 38.6 m/s (75 kts) The actual zonal wind field at 700 mb and the reproduction by summing all 527 modes are shown in Fig. 10. The reproduction of the original field is seen to be exact. If the eigenvector matrix were to be used to generate coefficients for a case not included in the dependent sample, the reproduction produced by summing over all modes would not be exact. The fields obtained by summing

the first 5, 15, 25 and 35 are shown in Figs. 11 and 12. When only five modes are summed, only the gross patterns (positive flow versus negative) are reproduced. Yet, it is interesting to observe how only five coefficients and modes can begin to recreate a particular field using eigenvectors derived from all 682 cases. As the number of modes is increased, an increasing amount of the complexity of the original field is replicated (Figs. 11 and 12). In the next chapter, the EOF coefficients derived for the zonal and meridional wind fields will be used as potential predictors representing the synoptic-scale forcing in a stepwise regression procedure.

V. REGRESSION ANALYSIS

A. MOTIVATION

Regression analysis is one of the most widely used statistical tools. Its essence is the study of relationships among variables to serve three major purposes: description, control and prediction. The researcher's goal is to find a simple mathematical model that, on the basis of observed data, will fit a complex phenomenon. An excellent presentation of theory and method that is conducive to practical application is given by Neter and Wasserman (1974). A more advanced presentation of statistical theory of the complete general linear model is given by Graybill (1976). Briefly, regression analysis involves using a linear combination of known quantities (predictors) to estimate the value of an unknown quantity (predictand).

EOF coefficients have been demonstrated to give a convenient, quantitative representation of physical forcing mechanisms acting on tropical cyclones (Chapter IV). Previous studies (described in Chapter I) have shown that statistical forecast schemes based on regression equations are viable methods. In particular, it is possible to use EOF coefficients based on geopotential heights as predictors to forecast tropical cyclone movement (Shaffer and Elsberry, 1982; Shapiro and Neumann, 1984). The hypothesis here is that the EOF coefficients derived to represent wind forcing of a tropical cyclone would be useful predictors of future storm movement.

Western North Pacific tropical cyclone position forecast errors for 10 years (1966-1975) have been statistically analyzed (Jarrell et al., 1978). The examination of errors

revealed that a small number of readily available parameters can classify, with reasonable effectiveness, a tropical cyclone forecast as representing a group of storms with either markedly above or below average errors. These variables include storm location, maximum sustained wind and the components of motion. Thus, it is hypothesized that these parameters might also be appropriate predictors of tropical cyclone movement. Regression analyses were performed to investigate these hypotheses.

B. VARIABLE AND CASE SELECTION

A primary goal of any regression analysis is to choose a set of independent variables that is "best". Here the criterion "best" is defined as minimizing the sum of squares of residuals without overfitting. Practicality requires that there be a scope of the model; that is, the coverage of a model is restricted to some region or interval of values of the independent variables. Model coverage is determined by the dependent cases included in the analysis. Possible difficulties are considered later in this chapter.

Predictands for this study are the average 24-, 48- and 72-hour zonal and meridional translation speeds of the tropical cyclone. These average speeds were determined from the base-time JTWC warning position and the subsequent JTWC warning position at 24, 48 or 72 hours. Positive motion was defined to the north and to the west, since the majority of tropical cyclones tracked to the north and west. As there are six predictands, six regression equations are required for each of the pressure levels included in the study (700 mb, 400 mb and 250 mb). A total of 18 equations was derived.

It is emphasized that the predictands were computed using JTWC <u>warning positions</u> at both base time and the

VII. CONCLUSIONS AND SUGGESTED RESEARCH

The results described in this thesis must be regarded as preliminary. However, it appears sufficiently promising that a viable, efficient regression scheme involving EOF coefficients to represent wind forcing can be developed. Two improvements are suggested before any operational testing might be performed. First, the predictands should be computed using the JTWC warning position at base time and the JTWC best-track positions at the predictand times. The best-track positions are based on a post-season analysis using all information available. The use of warning positions for the locations of the cyclone at predictand times unnecessarily contaminates the predictands. It is appropriate to use the warning position to locate the tropical cyclone at base time because this is the only position available at the time of the forecast. Second, forecast error should correspondingly be defined as the deviation of the forecast position from the best-track position.

Adoption of an operational forecast model requires testing using both dependent and independent data. The EOF-regression forecast errors should be compared with forecasts obtained by another operational model (such as CLIPER) and of the JTWC. The ultimate utility of the model depends upon demonstrated forecast skill for operational data, regardless of prior performance on dependent data or indications of a statistical significance test. Results obtained in the present study indicate very good potential for an operational model.

movement forecast could be generated upon input of the appropriate zonal and meridional components at the 527 points. Operational implementation of such a statistical-climatological method appears to be feasible.

Assuming that the eigenvector matrix E was determined from an adequate (large) dependent data set, the same set of eigenvectors can be used indefinitely for independent cases (new tropical cyclones), within the limitations of the scope of the model. Shaffer (1982) recommended that the regression equations be updated at the conclusion of each typhoon season. The feasibility and necessity of updating can be questioned for the current model. Shaffer's cases required 120 data points per case as opposed to two fields of 527 data points each for this study. If each case meeting selection requirements were added to the dependent data set, computing difficulties would be likely to become prohibitive after several tropical cyclone seasons. While it "might" be advantageous at least to include the anomalous cases, specific inclusion of anomalous cases could seriously reduce the ability of the regression analysis to obtain a good fit. Shaffer (1982) also suggested that increasing the number of dependent data cases should result in fewer large forecast errors. However, a larger dependent data set does not imply a better fit (as measured by R^2), nor does it imply that the model will better forecast anomalous cases. One alternative would be to have more than one set of regression equations. A map-typing or analog technique could be used to determine which set of equations would be appropriate on a case-by-case basis. Such an alternate method would lack simplicity, which is one of the most attractive features of the current EOF-based regression forecast scheme.

The forecast scheme using EOF-based regression models is very simple compared with other more elaborate models. The model requires only a set of coefficients representing the synoptic-scale wind forcing and predictors representing present position and past storm movement. The entire forecast scheme could be executed using a minicomputer. The

for the new case. If n is large, the term $(1/n+1)$ in (6.1) is negligible relative to the first term so that the following approximation is valid:

$$R(\text{new}) \sim R(\text{old}) \quad . \qquad (6.2)$$

The eigenvalues and eigenvectors computed for the dependent data using R(old) should be almost identical to those obtained from computation using R(new). Provided that a sufficiently large dependent sample is available, it is reasonable to use R(old) to compute the EOF coefficients for a new data case and then to use these coefficients as predictors in the forecast equations derived with the dependent data. Shaffer (1982) determined that use of the coefficients for cases calculated using R(old) introduced very little error into the movement forecast. Testing is required to determine a sample size sufficient for (6.2) to be valid. The reader is referred to Shaffer for a detailed example of methodology appropriate to test these observations.

Operational implementation of an EOF forecast scheme would be straightforward. Two major operations are required. First, the 35 required EOF coefficients for the independent data cases must be computed and stored. This involves multiplication of the 35 x 527 transpose matrix of truncated eigenvectors and the 527 x 1 vector of standardized observations. It is assumed that no significant error would be associated with using the means and standard deviations from the dependent sample at the equidistant grid points. Second, these coefficients and other predictors would be substituted into the regression equations to predict the average zonal and meridional speeds for the forecast interval. The predicted future location of the tropical cyclone could then be determined.

VI. POTENTIAL FOR USE WITH INDEPENDENT DATA

Based on results obtained using dependent data and predictands derived using warning positions, EOF-based regression forecasting appears to have potential for improved prediction of tropical cyclone movement. The value of the final model depends upon its potential for operational use with independent data. The regression equations were derived using EOF coefficients computed using a particular set of eigenvectors; namely, the eigenvector matrix E of the dependent data set. These regression equations are applicable only for tropical cyclone cases within the scope of the model. The scope of the model is determined primarily by the values of the predictors and predictands used to derive the forecast equations. EOF coefficients are the most sensitive predictors in that they are derived from the particular flow fields surrounding the tropical cyclones. For a new case, the eigenvectors no longer exactly represent the maximum variation in all of the observations--dependent set plus the new case. The stability of the eigenvectors must be examined by determining whether the eigenvectors and coefficients of the dependent data cases remain nearly the same if a new case is added.

Inclusion of an additional case changes the correlation matrix R. The new correlation matrix can be computed by:

$$R(new) = [n/(n+1)] \cdot R(old) + [1/(n+1)] \cdot zz' \quad , \qquad (6.1)$$

where R(new) is the new correlation matrix after addition of the new case, R(old) the original correlation matrix of the dependent data, n the number of cases prior to inclusion of the new case, and z the m x 1 vector of standardized data

Multicollinearity exists unless the variables (including the EOF coefficients) are completely pairwise uncorrelated. This rarely occurs naturally. When the independent variables are highly correlated, the predictive ability of the model is suspect for new cases whose independent variables deviate from the pattern of multicollinearity in the dependent cases.

errors. These results do not appear to agree with Jordan (1952) and Miller (1958) who were unsuccessful at using winds and heights at upper tropospheric levels to describe tropical cyclone motion.

It was also important to examine the results for consistency in the forecasts. Consistency would be indicated by small standard deviations of forecast error. The standard deviations were generally comparable to Shaffer (1982). There were no significant differences among the standard deviations for a given forecast interval, except the standard deviation for the 72-hour forecast using the 250 mb equation was particularly smaller than that for either 700 mb or 400 mb equations.

D. CAUTIONS FOR USE OF THE REGRESSION MODEL

Various restrictions should be considered when applying the results of a regression analysis. The validity of the predictions depends upon whether basic causal conditions at later times will be similar to those in effect for the data used for the regression analysis. The scope of the data must be respected to avoid inferences based on an independent variable which falls outside the range of input data. Finally, it must be remembered that the predictands used to derive the equations were computed using the JTWC warning positions at both the base time and at subsequent forecast times.

The performance of the model as indicated by the dependent sample may be superior to the ability for new cases. This is known as prediction bias, which results when the final model chosen is too uniquely related to the input data cases. It is emphasized that the models developed in this study have not been tested with independent data cases.

forecast interval. Finally, the forecast error was computed by determining the magnitude of the vector between the forecast position and the JTWC warning position at the corresponding time.

The forecast errors are summarized in Table XVII by pressure level and forecast interval. It is stressed that these results were derived using only the dependent cases. As expected, the forecast error increases with increasing length of forecast interval. However, the magnitudes of the increases are reasonable. The increase in the 72-hour forecast error over the 48-hour forecast error was much smaller than that for Shaffer's (1982) dependent sample. The smallest change for the current study was about 82 km less than for Shaffer's results. It was previously noted that there was a rapid decrease in R^2 with increasing forecast interval for Shaffer's equations. Shaffer's equations predicted short-term movement well, but the errors grew rapidly with increasing time. The 24-hour forecast error for this study was about 25 km larger than for Shaffer's dependent sample. However, the best 48- and 72-hour forecast errors for the current study were 28 km and 90 km less than those of Shaffer. Stability of predictand variance for the current study resulted in models that give promise of improvement of long-term forecasts.

There were no overwhelming differences in performance of the equations derived for the three levels at any forecast interval. Shaffer's (1982) forecast equations based on an EOF analysis of geopotential height at 500 mb, 700 mb and 850 mb also did not have significant differences in errors among the three levels. However, Shaffer's 500 mb equations outperformed the other two equation sets by a wide margin for a small set of independent cases. Although the 72-hour forecast errors in Table XVII are largest for the 250 mb equation, they still compare favorably with the JTWC mean

procedure for 15 of the 18 equations, including all nine of the 24-hour forecast equations. For the zonal 48-, zonal 72- and meridional 72-hour forecast equations, the second or third variable selected was for past movement. The predictors UOLD2, UOLD3, VOLD2 and VOLD3 (see Table VIII for description) were most frequently chosen. These results were in agreement with Neumann's (1978) observation that statistical screening techniques invariably select present and past storm movement over steering predictors derived from the surrounding flow for short-term tropical cyclone movement. However, the predictions are not simply persistence forecasts. Mode variables CU1, CU2, CV1 and CV2 were often the second, third or fourth predictors selected. This was not surprising since the first 2 modes account for the largest percentages of variance in the wind-component fields. From 2 to 10 zonal EOF coefficient predictors and from 2 to 7 meridional EOF coefficient predictors were chosen for the forecast equations, so that wind forcing was also found to be an important determinant of tropical cyclone movement.

Several potential predictors were not included in any of the equations: DATE, CINT, VOLD1 and DISP1. The potential predictor UOLD1 was retained in only one forecast equation. These past movement variables represent the interval from 24 to 12 hours prior to base time. Very little information would be lost by exclusion of these potential predictors.

The potential performance of this regression forecast scheme was evaluated by testing on the dependent data cases. The following procedure was applied for the forecast intervals 24, 48 and 72 hours at each pressure level (700 mb, 400 mb and 250 mb). First, the appropriate equations were used to predict the average zonal and meridional speeds of the tropical cyclone. These speeds were converted to zonal and meridional displacements of the tropical cyclone during the

same magnitude indicates mean movement to the northwest. The values of R^2 for the zonal equations were significantly greater due to the larger variability in zonal movement.

Values of R^2 do not vary greatly with forecast interval for either the zonal or meridional equations at any of the pressure levels. The largest deviations are for the 700 mb zonal equations and the 250 mb meridional equations. In contrast, Shaffer's (1982) regression equations consistently displayed a significant decrease in the value of R^2 with increasing forecast interval (about 0.1 per 12 hour interval). These differences in the variation of R^2 with forecast interval may account for differences in forecast error characteristics discussed later in this section.

Finally, the accuracy of the zonal or meridional equations is not a strong function of pressure. For either the zonal or meridional movement, the equation derived using the EOF coefficients for a given level does not perform significantly better (as measured by R^2) than the equations for the other two levels. This was similar to results obtained by Shaffer (1982) for the dependent sample. Slightly larger values of R^2 are found for the 700 mb zonal equations at all three forecast intervals.

Tables XI through XVI summarize the regression equations. The first value in each table is the intercept. The average speed component (km/hr) is obtained by summing the product of all non-zero regression coefficients and the values of the associated variables. Parsimony in selection of variables was met; the main purposes of retention of as few variables as possible were to obtain simple equations and to avoid overfitting.

Several observations were made regarding the variables retained for the regression equations and the order of selection. A past movement variable (predictors 5-10 in Table VIII) was the first variable selected in the stepwise

independent variables in the regression model. This statistic is defined:

$$R^2 = SSR/SSTO = 1 - (SSE/SSTO) , \qquad (5.1)$$

where SSTO is the total sum of squares, SSR is the regression sum of squares and SSE is the residual sum of squares. The R^2 statistic measures the proportion of the total variation in the predictand associated with the use of the independent variables. The regression equations retained only those predictors which resulted in an increase in R^2 of at least 0.01.

The value of R^2 for each regression equation is given in Table IX. Matching forecast times and pressure levels, the value of R^2 for a zonal equation is always at least 0.12 greater than the R^2 for the meridional equation for the same forecast interval and pressure level. Shaffer (1982) found differences as large as 24 percent. The zonal regression equations account for a greater portion of the total zonal movement variation than the meridional equations. This observation agrees with Shaffer (1982). At least 59 percent of the total variation in zonal movement was accounted for by the equations at each of the three pressure levels for any forecast interval. Values of R^2 for the meridional equations range from 0.325 for the 250 mb 72-hour forecast to 0.475 for the 700 mb 24-hour forecast.

The greater predictive ability of the zonal equations was expected. First, it was shown in Chapter IV that fewer modes were required to describe the zonal wind than the meridional wind. Second, there is greater variation in the zonal movement than in the meridional movement. The means and standard deviations of the average zonal and meridional speeds of the various forecast intervals are given in Table X. Positive mean zonal and meridional components with the

cases for regression analysis. Sample sizes were 409, 308 and 232 cases for the 24-, 48- and 72-hour equations, respectively.

C. THE EQUATIONS AND ERROR ANALYSIS

A linear stepwise regression analysis was chosen to derive equations to predict future average zonal and meridional speeds of the tropical cyclones. Although an a priori assumption of linearity could not be made, the number of polynomial predictors generated from a base set of 83 potential predictors would have been intractable. The UCLA biomedical computer program BMDP2R (Dixon and Brown, 1979) was used for the regressions. Multicollinearity, which occurs when some or all of the independent variables are highly correlated (Neter and Wasserman, 1974), was avoided by the use of stepwise regression. Multicollinearity fosters a large potential for overfitting since many different models would provide the same good fit. As a result, it becomes impossible to interpret any one set of regression coefficients as being representative of the effects of the different independent variables. Also, the estimated regression coefficients usually have a very large sampling variability so that they are imprecise and lose their meaning (or significance). The BMDP routine includes a preset tolerance to automatically screen the variables at each step. A potential predictor was not allowed to enter the model if it was highly correlated with any predictor chosen in earlier steps. To ensure that a predictor was significantly (in a statistical sense) correlated with the predictand, a minimum F-to-enter value of 4.0 was imposed (Dixon and Brown, 1979).

The coefficient of multiple determination (R^2) is a measure of the association between the dependent and

The recent motion of the storm is an integral part of the prediction model of nearly all tropical cyclone forecast methods. Most cyclones move with uniform direction and speed (Gray, 1978). Satisfactory forecasts of tropical cyclone movement can be based mainly on extrapolation and climatology. Because there are relatively few storms with anomalous tracks, predictors based on present and past movement tend to dominate a statistical analysis of storm motion. These "difficult" storms, which are associated with above-average forecast errors, tend to recurve or to move erratically with nonclimatological tracks. A persistence-climatology forecast leads to large errors for the 20-25 percent of the cases of anomalous motion (Gray, 1978). When there are not many storms during a season, a single anomalous storm can result in a significant bias of the yearly mean forecast error (Neumann, 1981).

The remaining potential predictors are related to observations of the tropical cyclone at base time. Tropical cyclone intensity (potential predictor 4, Table VIII) was the JTWC warning maximum sustained wind speed at base time. The Julian date and the JTWC warning position latitude and longitude (potential predictors 1, 2 and 3, Table VIII) completed the set of potential independent variables.

The 682 cases from the EOF analysis were used to select the cases for the regression analysis. For a case to be included, a complete set of potential predictors had to be available. In addition to availability of the GBA, the JTWC reports had to be available at 12 and 24 hours prior to base time and at least 24 hours subsequent to base time. Similarly, selection of that case for development of regression equations for 48- or 72-hour forecasts required that JTWC warning positions be available at 48 or 72 hours, respectively. These requirements decreased the number of

forecast times. In the subsequent discussion, comparisons of the results obtained in this study for the dependent data are made with those obtained for the dependent data in Shaffer's (1982) study based on an EOF analysis of geopotential height. Shaffer's predictands were computed using the JTWC warning and best-track positions at base and forecast times respectively.

Predictors were sought to assess quantitatively the effect of five factors on tropical cyclone movement: (1) external (to the cyclone) physical forcing; (2) previous cyclone movement; (3) cyclone intensity; (4) date; and (5) initial (warning) position. Table VIII describes the 83 potential predictors used for the regression analysis and identifies these predictors by name and number. The potential predictors were identical for all 18 regression equations, except that the regression equation for a specific level included only the EOF coefficients at that level.

Synoptic external forcing on a tropical cyclone has been conjectured to be an important determinant of cyclone movement (Brown, 1981; and others). To incorporate quantitatively the wind forcing, the EOF coefficients associated with the first 35 zonal and meridional modes were selected as potential predictors. These coefficients are potential predictors 14 through 83 (CU1 through CU35 and CV1 through CV35) in Table VIII. An important objective of this study was to evaluate how well these EOF coefficients represented atmospheric features that affected cyclone movement.

Persistence has long been known to be a good predictor of short-term tropical cyclone motion. Therefore, nine potential predictors representing past zonal and meridional motions were included. These were variables 5 through 13 in Table VIII. Each prior average speed or vector displacement was based on JTWC warning positions to simulate operational conditions.

The following discussion suggests other possible research to improve the operational model:

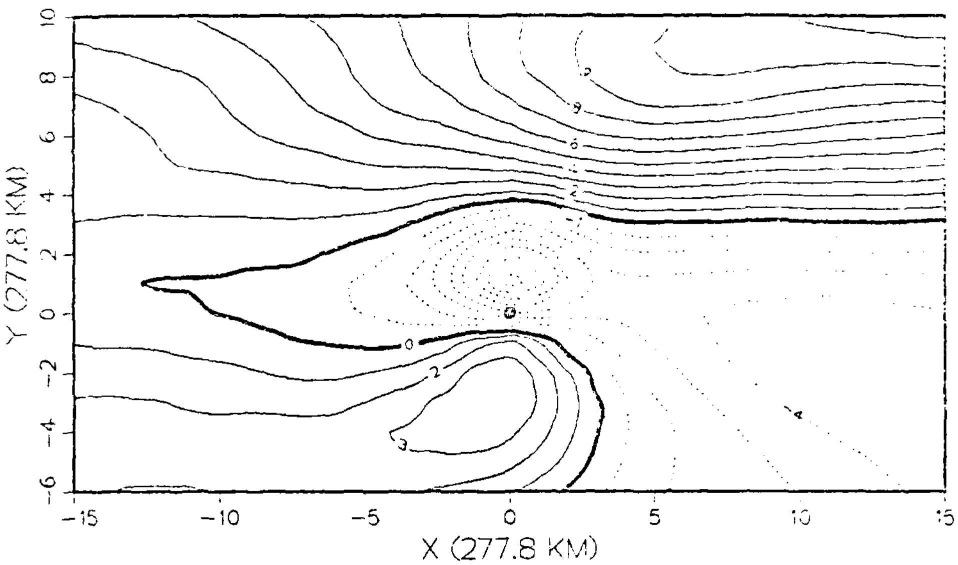
1. The forecast scheme could be improved if other variables representing physical features affecting storm movement could be identified and included in the regression equations. Intensity, represented by maximum sustained wind speed, was found to be an unimportant predictor in both this study and Shaffer's (1982). Following Chan and Gray (1982), variables such as the size of the cyclone should be tested in the regression analysis. Model verification of George and Gray's (1976) observation that the 700 mb level best specifies cyclone speed and that the 500 mb level best specifies cyclone direction might be attempted.
2. The EOF-based regression forecast scheme is not limited to input of coefficients derived from analyses. Coefficients derived from prognostic data fields, such as a 24-hour forecast from a dynamic numerical prediction model, might improve the longer range f recasts.
3. Each EOF coefficient represents the contribution of the associated eigenvector to the total forcing. The resultant tropical cyclone movement is a summation of the total forcing by all modes. Additional insight into the more important modes for tropical cyclone forcing could possibly be obtained by examination of the correlation of the modes with the tropical cyclone movement.
4. Vertical coupling might be represented in the EOF modes for the three levels. Testing would involve the development and analysis of regression models using EOF coefficients from more than one pressure level in various combinations.

5. The zonal and meridional components of tropica cyclone movement are forecast separately by the current scheme, even though tropical cyclone movement is a vector quantity. Correlations exist between the zonal and meridional components of motion (Shapiro and Neumann, 1984). Improvements might arise from inclusion of potential predictors which account for the correlation between the zonal and meridional components of motion. Also, an operational model might be improved using a grid rotated along the direction of cyclone motion (Shapiro and Neumann, 1984).
6. A vector EOF analysis may improve the identification of forcing modes for tropical cyclone movement. Rotation of the eigenvectors could also be investigated for potential improvement of the method. As previously noted, more eigenvectors may have to be retained to guard against underfactoring.

The EOF-regression model definitely shows promise for improvement of operational forecasts of tropical cyclone movement. This simple regression model performed very well on dependent data. Additional reductions in forecast error may be possible through inclusion of more sophisticated physical forcing parameters and prognostic fields. Further research appears warranted.

APPENDIX A

FIGURES



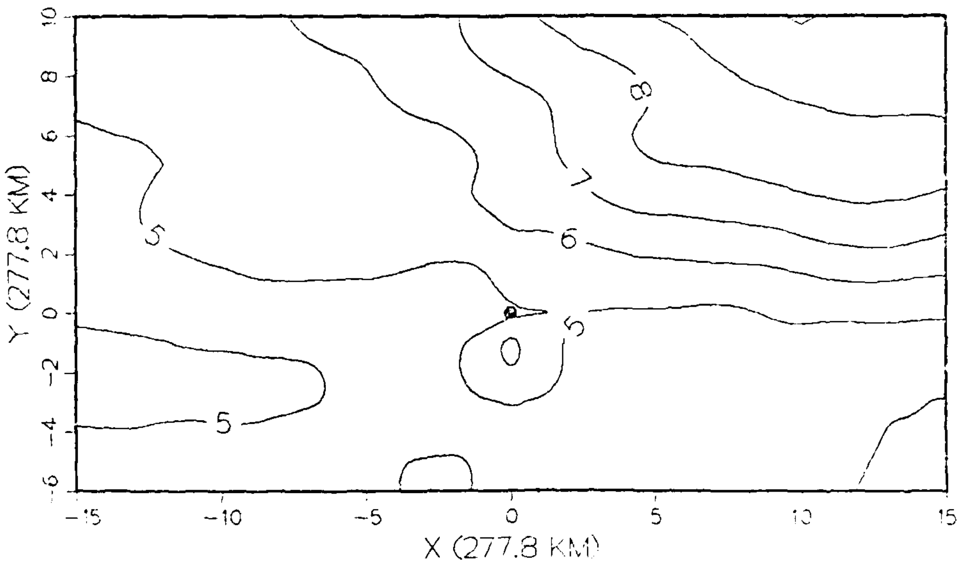


Fig. 1. Mean (top) and standard deviation (bottom) of 700 mb zonal wind (m/s). Black dot is storm center. Negative contours are dashed. The zero contour is a heavy solid line.

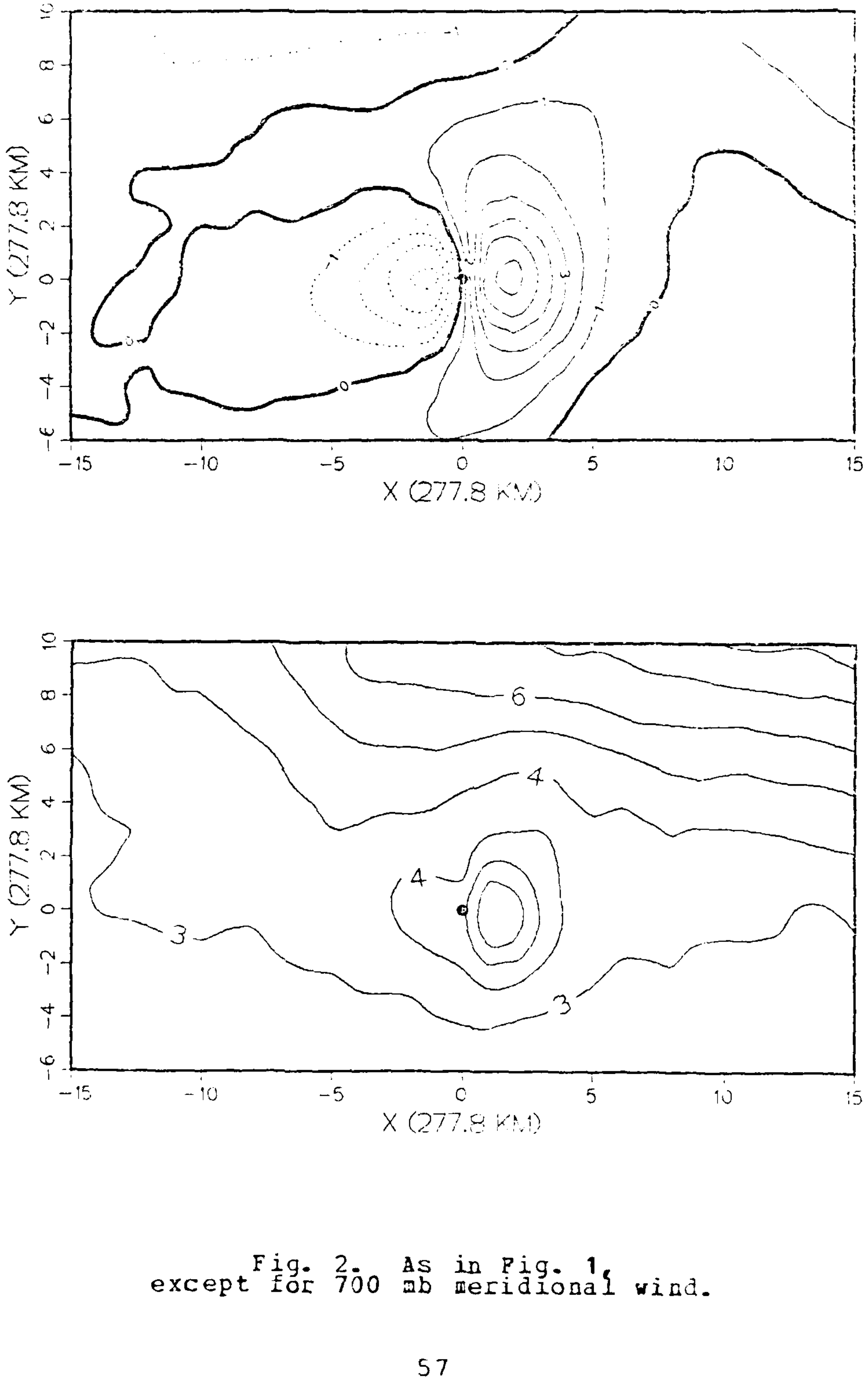
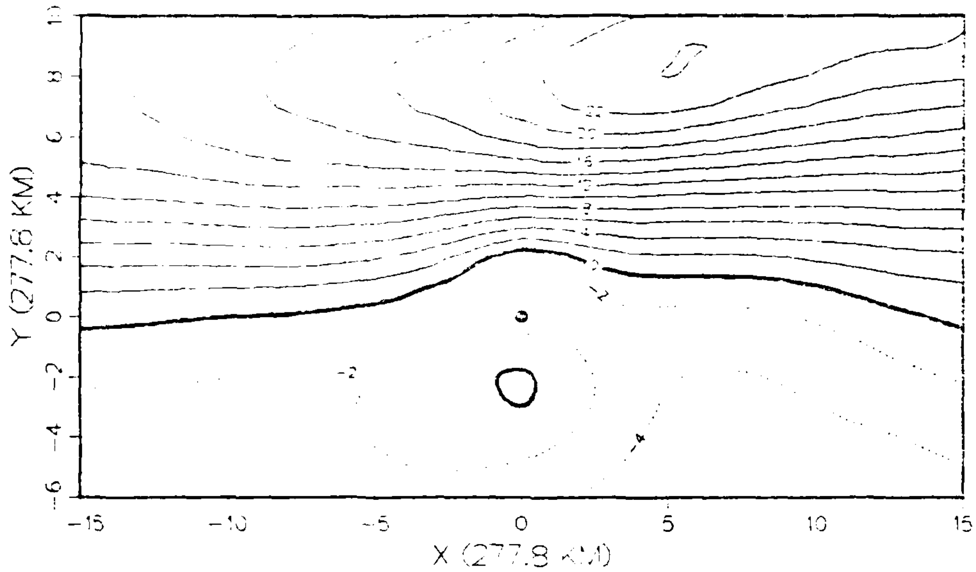


Fig. 2. As in Fig. 1, except for 700 mb meridional wind.



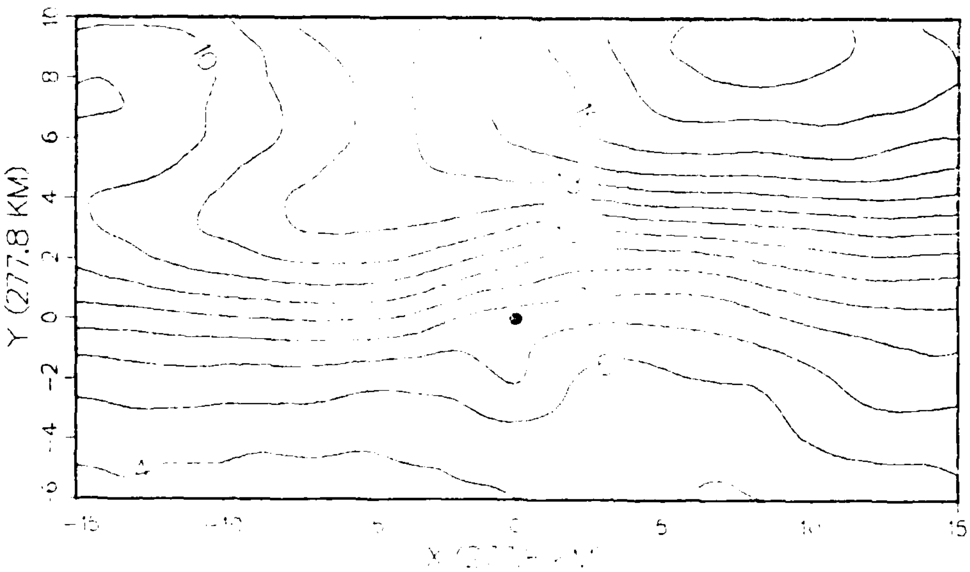


Fig. 3. As in Fig. 1, except for 400 mb zonal wind.

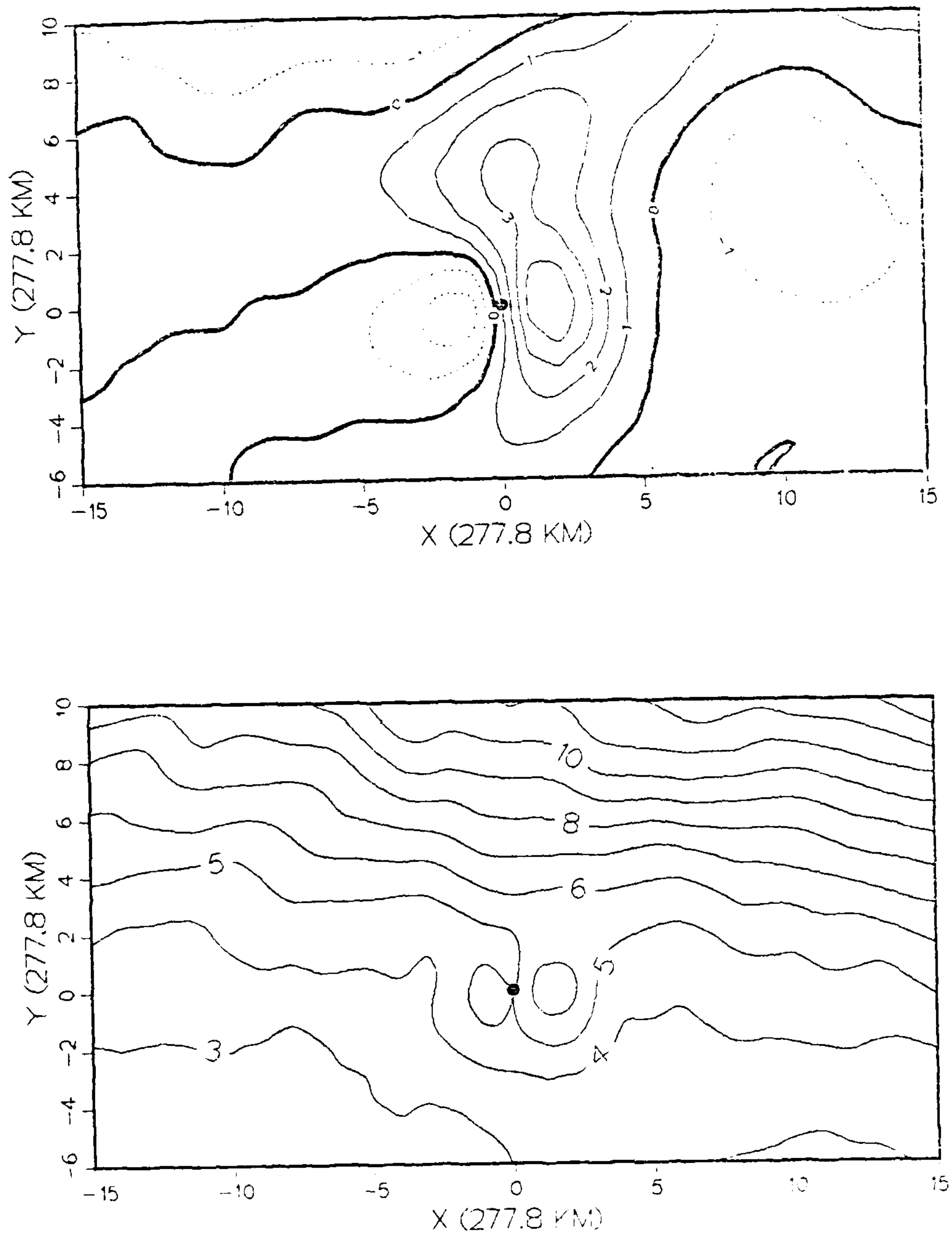


Fig. 4. As in Fig. 1, except for 400 mb meridional wind.

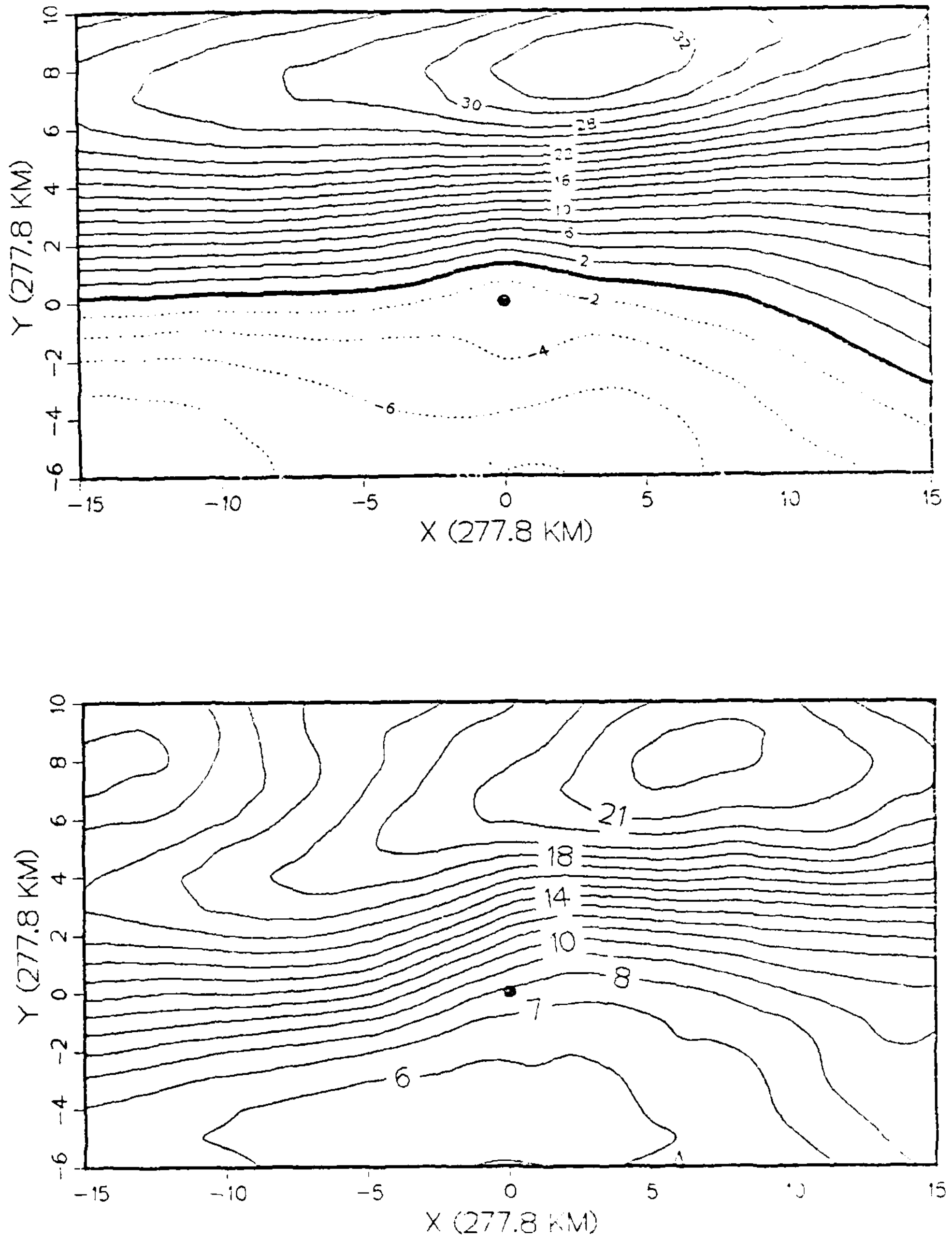


Fig. 5. As in Fig. 1, except for 250 mb zonal wind.

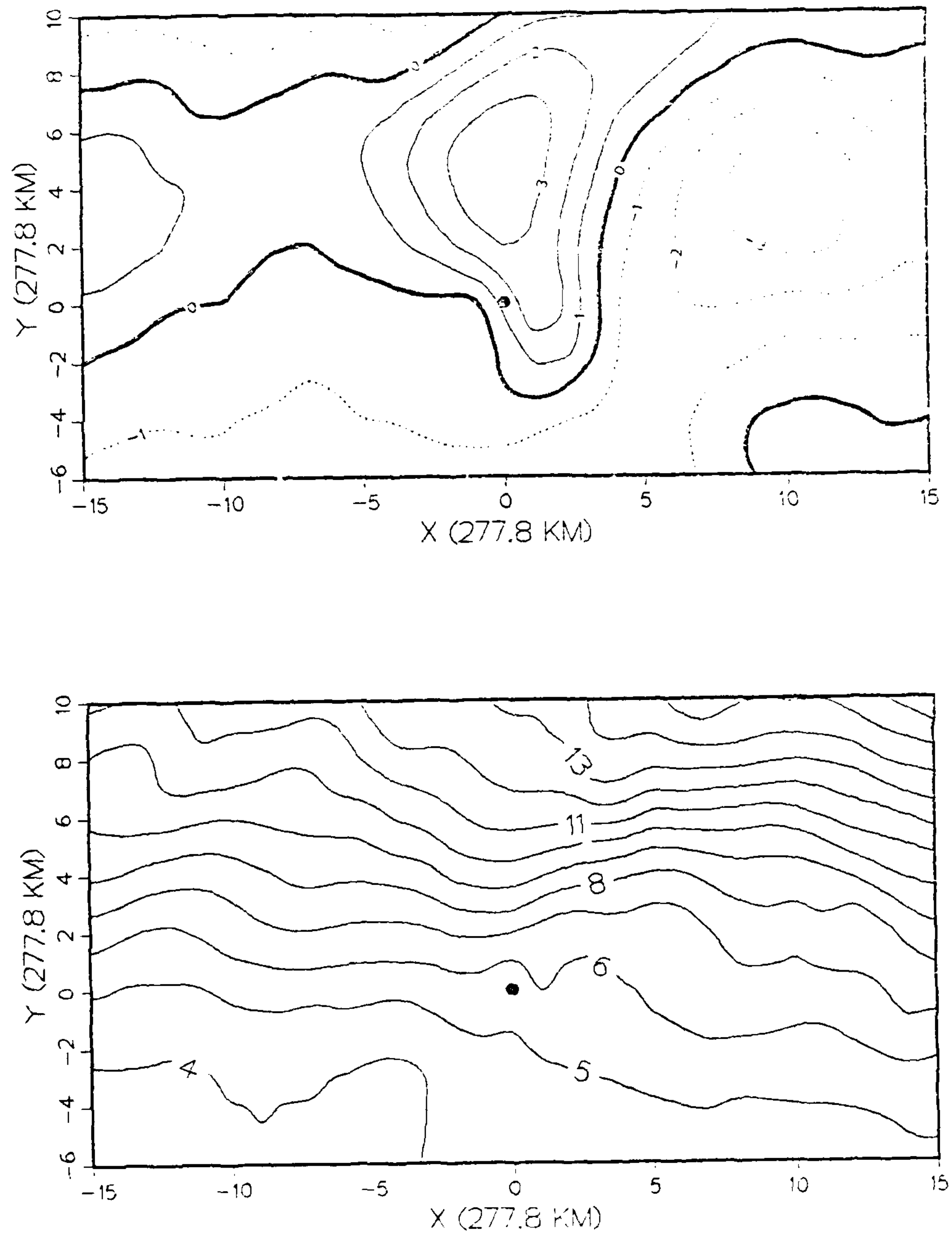


Fig. 6. As in Fig. 1, except for 250 mb meridional wind.

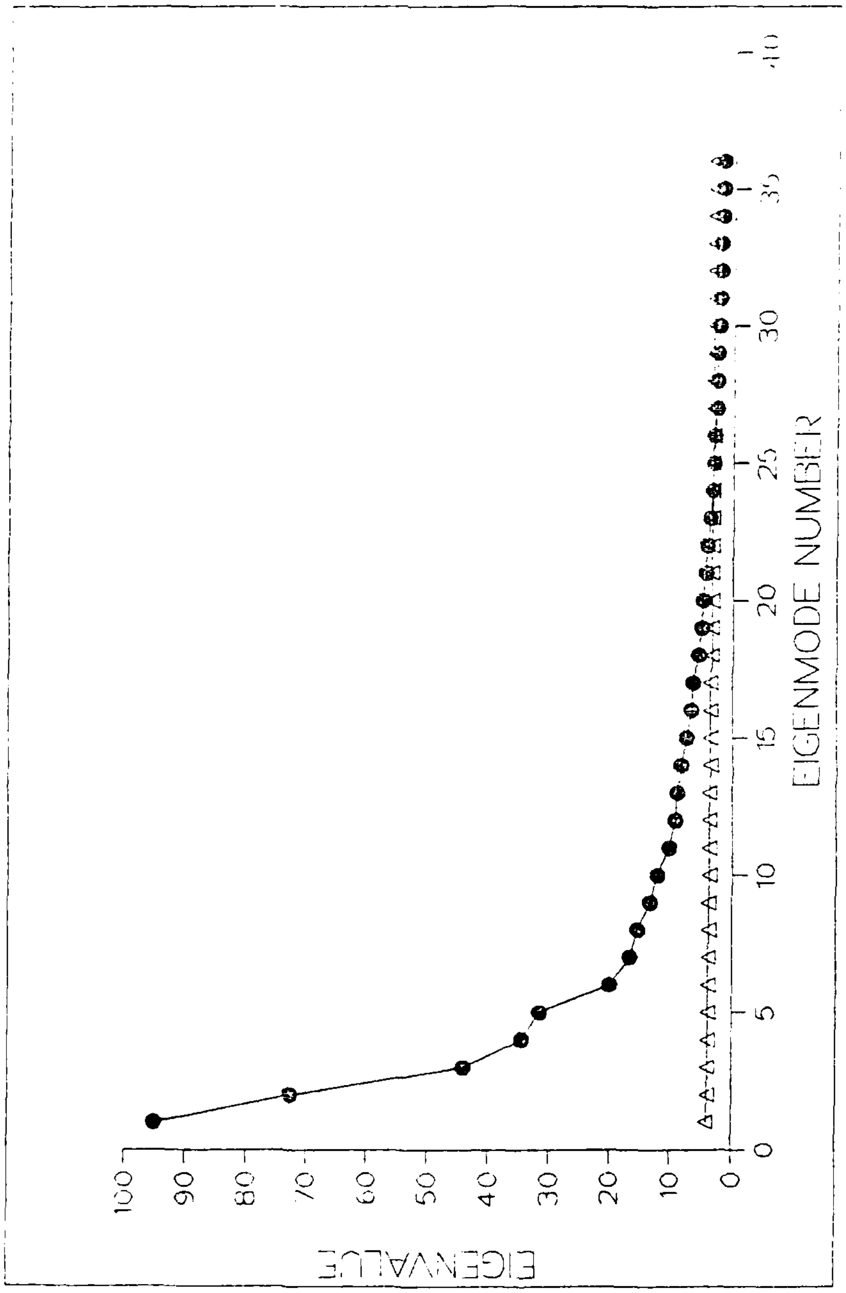


Fig. 7. Eigenvalues of 700 mb zonal modes (circles) and Monte Carlo mean eigenvalues plus two standard deviations (triangles).

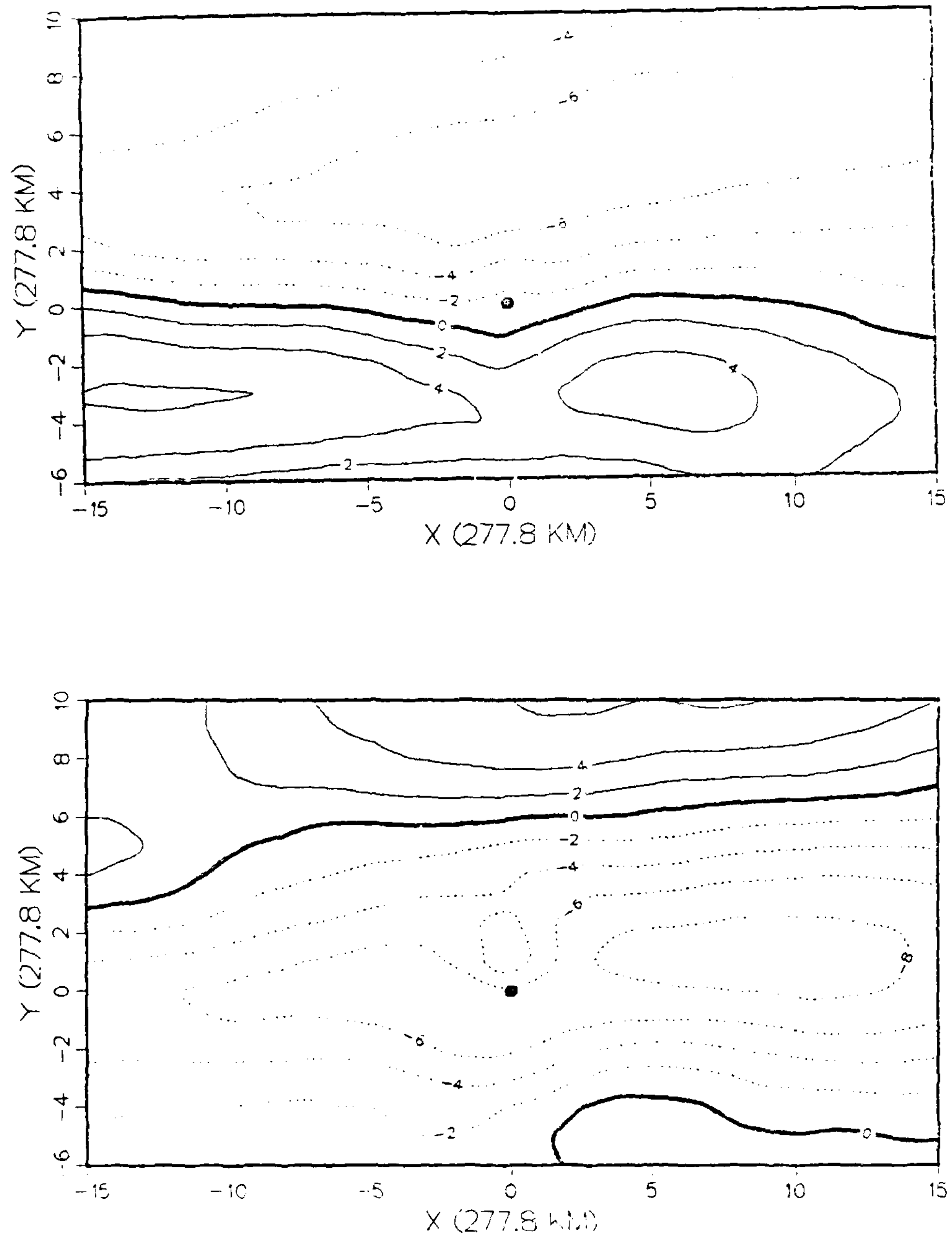


Fig. 8. 700 mb zonal eigenmodes 1 (top) and 2 (bottom) multiplied by 100. Negative values are dashed.

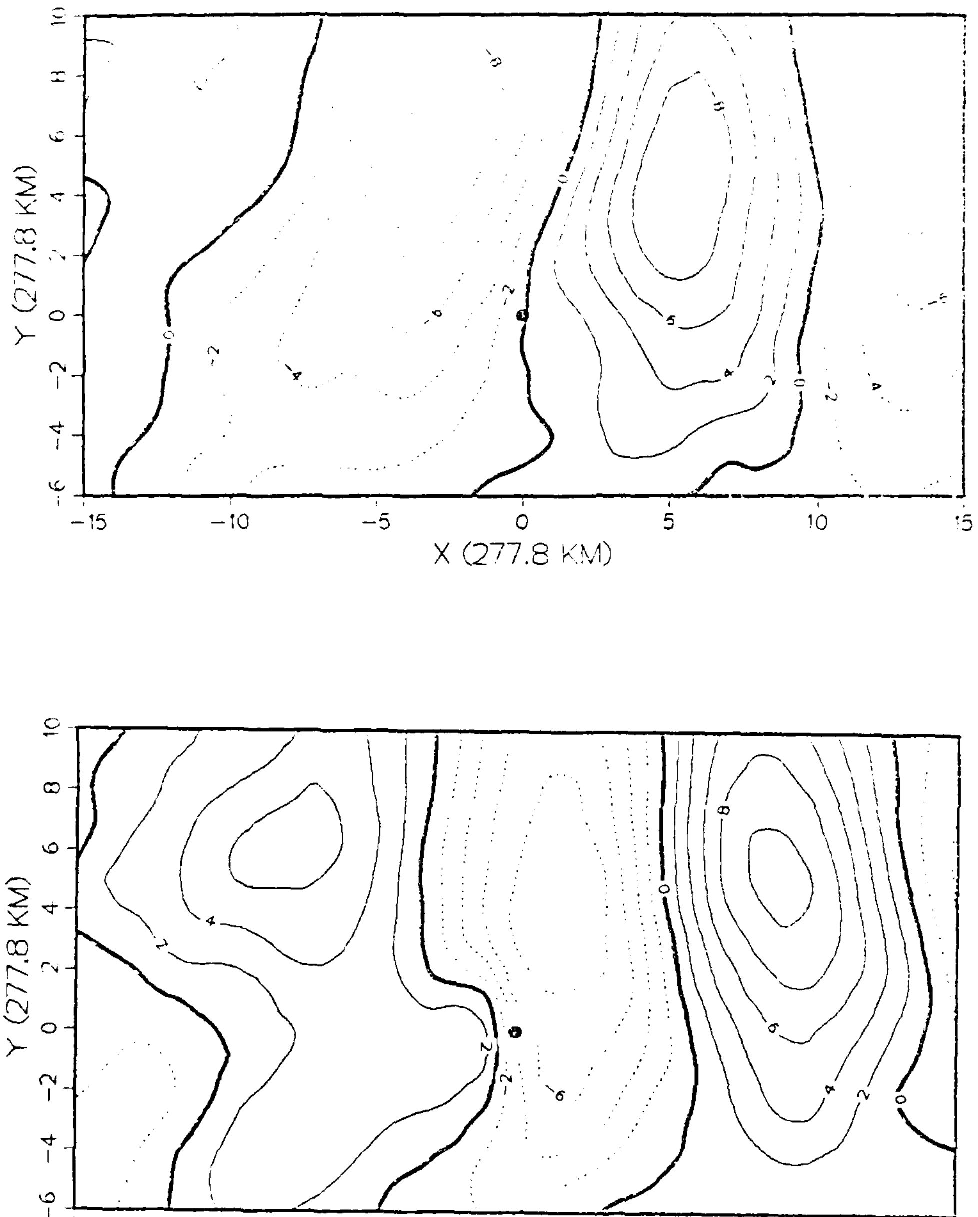


Fig. 9. As in Fig. 8, except for 700 mb meridional eigenmodes.

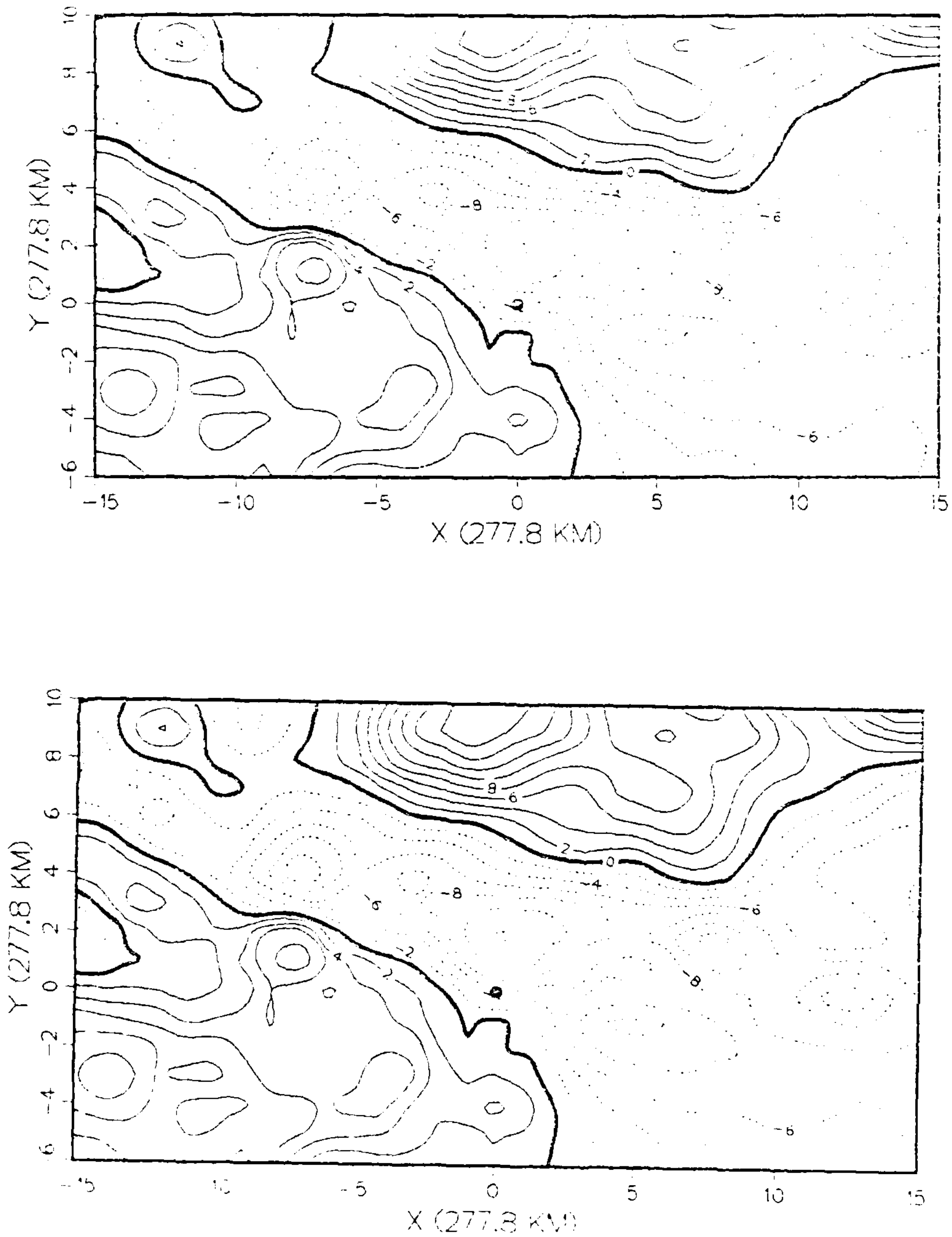


Fig. 10. 700 mb zonal wind for
Typhoon Hope at 0000 GMT 30 July 79 (top)
and its reconstruction (bottom) using all 527 modes.

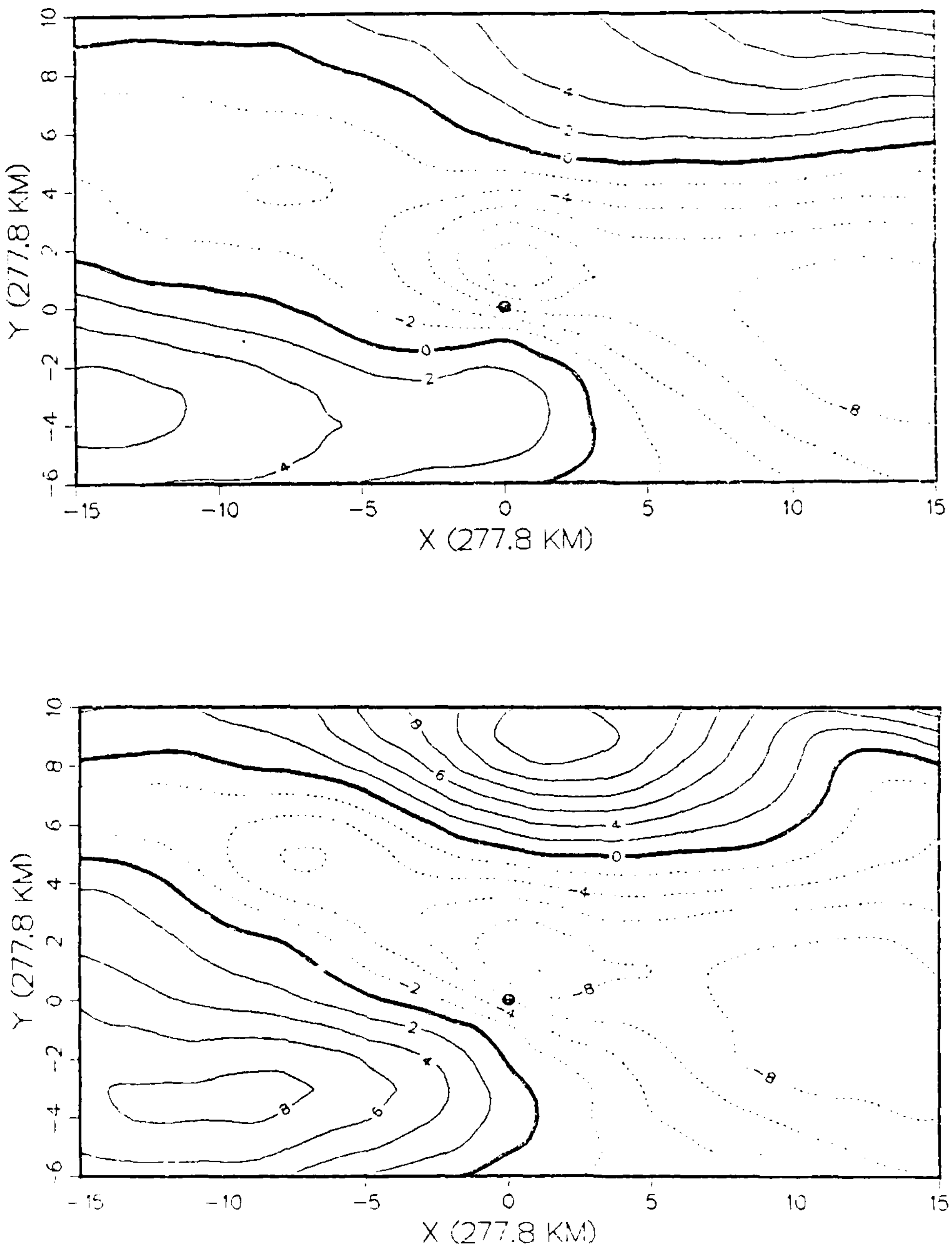


Fig. 11. Reconstruction similar to Fig. 10, except 5 modes (top) and 15 modes (bottom) are used.

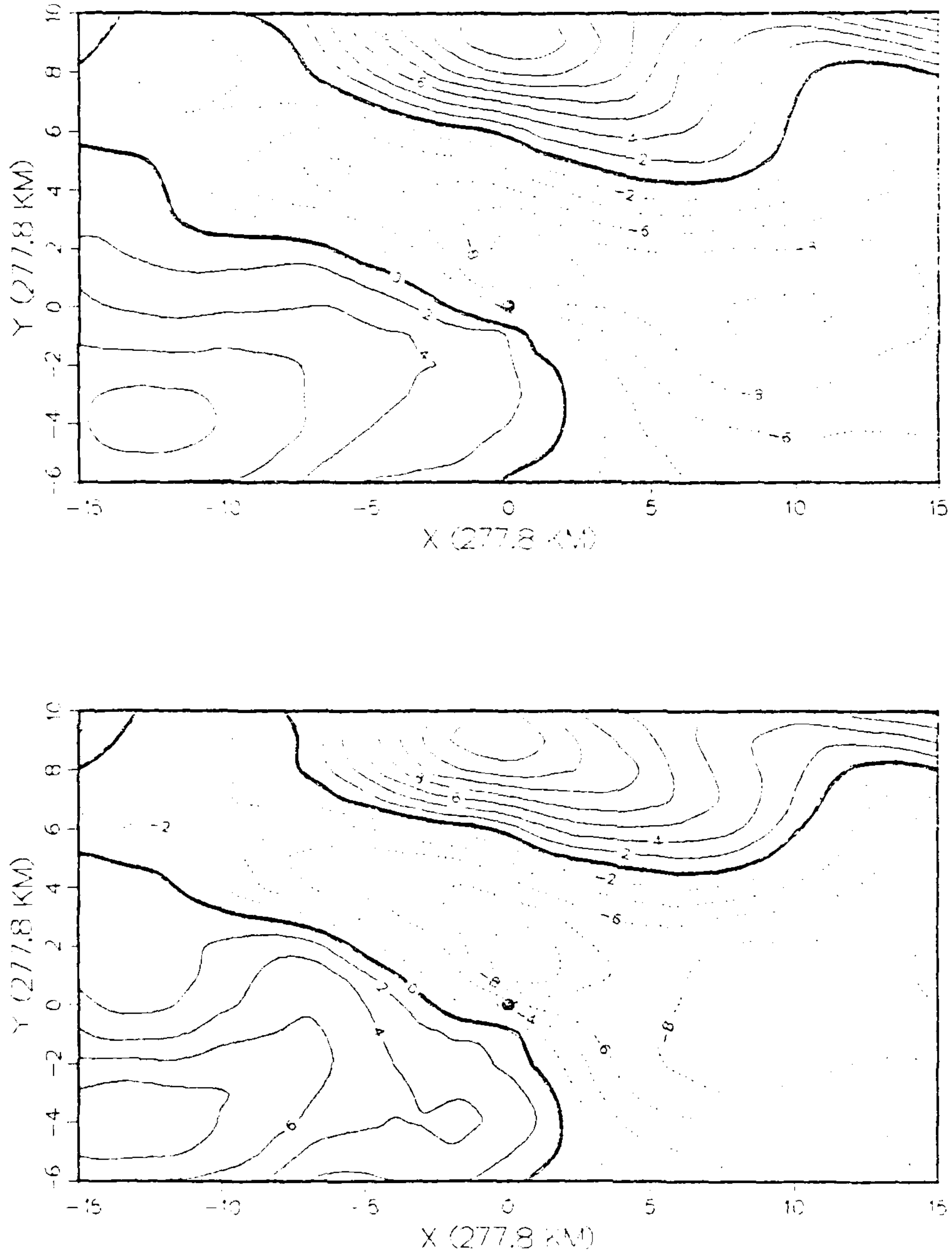


Fig. 12. Reconstruction similar to Fig. 10, except 25 modes (top) and 35 modes (bottom) are used.

TABLE XVI

Intercept and regression coefficients for the meridional average speed equation using 250 mb EOFs.

FORECAST INTERVAL (H)

	24	48	72
INTERCEPT	6.8262	6.6448	6.0899
UOLD2	-0.0776	.0	.0
VOLD2	0.3989	0.2656	.0
VOLD3	.0	.0	0.2255
CU1	.0	.0	0.2161
CU5	0.2181	.0	.0
CU10	.0	0.5887	.0
CU25	.0	.0	-0.8033
CU26	.0	0.5864	.0
CV1	-0.1544	.0	-0.1733
CV2	-0.2741	-0.2411	.0
CV3	0.2210	.0	.0
CV5	0.2283	.0	0.2425
CV6	.0	0.2313	.0
CV9	-0.2988	.0	.0
CV11	.0	.0	0.3307
CV12	.0	-0.2143	.0
CV16	-0.3347	-0.3239	.0
CV17	.0	-0.3017	-0.3271
CV18	.0	0.2813	0.3346
CV20	.0	.0	0.3263
CV26	.0	-0.4296	.0

TABLE XV

Intercept and regression coefficients for the zonal average speed equation using 250 mb EOFs.

FORECAST INTERVAL (H)

	24	48	72
INTERCEPT	0.0172	-27.3931	-22.8406
CLAT	.0	-0.4879	-0.5434
CLON	.0	0.2827	0.2535
UOLD2	.0	0.3075	0.2259
UOLD3	0.5534	.0	.0
DISP2	0.0449	.0	.0
DISP3	-0.0218	.0	.0
CU1	0.4932	0.3131	0.1727
CU2	-0.3763	-0.3331	-0.2389
CU3	0.4395	.0	.0
CU4	.0	0.3436	.0
CU10	.0	.0	-0.7225
CU12	.0	-0.5748	.0
CU26	.0	.0	-1.0172
CV1	.0	0.5851	0.7922
CV3	-0.3831	-0.3128	.0
CV6	.0	.0	-0.5246
CV9	.0	.0	-0.3744
CV11	.0	-0.5210	.0
CV16	.0	0.6694	0.9332
CV27	.0	-0.6646	.0
CV28	.0	.0	0.6376

TABLE XIV

Intercept and regression coefficient for the meridional average speed equation using 400 mb EOFs.

	FORECAST INTERVAL (H)		
	24	48	72
INTERCEPT	6.3235	7.8935	7.1388
VOLD2	0.3748	0.2005	.0
VOLD3	.0	.0	0.1901
CU2	-0.1766	-0.2360	-0.1997
CU5	.0	-0.1852	.0
CU7	.0	-0.2726	.0
CU10	.0	0.3693	0.2350
CU13	-0.5186	-0.6135	-0.4330
CU22	.0	.0	0.5219
CU25	0.7326	0.7109	1.0265
CU29	.0	.0	-0.7744
CU31	.0	-0.6577	-0.7560
CU35	.0	.0	0.6557
CV2	-0.2634	-0.1785	.0
CV4	.0	.0	-0.2465
CV7	.0	0.2766	0.2098
CV8	.0	0.2584	.0
CV12	.0	.0	0.2765
CV15	.0	.0	0.2765
CV16	.0	-0.3967	-0.4005

TABLE XIII

Intercept and regression coefficients for the zonal average speed equation using 400 mb EOFs.

	FORECAST INTERVAL (H)		
	22	48	72
INTERCEPT	2.0174	-15.7644	-4.3064
CLAT	.0	.0	-0.4520
CLON	.0	0.1314	0.0974
UOLD2	.0	0.2379	0.1377
UOLD3	0.3266	.0	.0
DISP2	0.0398	.0	.0
DISP3	-0.0190	.0	.0
CU1	0.5621	0.6868	0.7350
CU2	0.9062	0.8759	0.7496
CU6	.0	.0	0.4717
CU11	.0	.0	-0.5958
CU25	-0.9854	-0.9190	-1.2793
CU28	.0	.0	0.8767
CV1	-0.4448	.0	.0
CV2	0.2838	0.4178	0.3366
CV16	.0	.0	0.3673
CV18	.0	.0	0.7152

TABLE XII

Intercept and regression coefficients for the meridional average speed equation using 700 mb EOFs.

	FORECAST INTERVAL (H)		
	24	48	72
INTERCEPT	6.0283	6.0252	5.4471
UOLD1	.0	.0	0.1836
VOLD2	0.3738	0.1458	.0
VOLD3	.0	.0	0.2115
DISP2	.0	.0	0.0193
DISP3	.0	0.0048	-0.0122
CU1	.0	.0	0.1048
CU2	.0	-0.1964	-0.1919
CU4	-0.1490	-0.1379	.0
CU5	.0	0.1661	.0
CU6	-0.2689	.0	.0
CU7	.0	-0.4349	-0.4106
CU8	.0	0.4148	.0
CU12	.0	-0.3181	.0
CU22	.0	-0.3317	.0
CU25	0.5253	0.7267	0.6355
CU26	.0	.0	0.5146
CV2	-0.4647	-0.3718	-0.3523
CV3	0.2861	.0	0.1796
CV7	.0	-0.2651	-0.2476
CV8	.0	-0.3642	-0.2000
CV9	.0	-0.2030	.0
CV13	.0	0.2525	.0
CV14	.0	.0	-0.2473
CV16	0.3149	.0	.0

TABLE XI

Intercept and regression coefficients for the zonal average speed equation using 700mb EOFs.

	FORECAST INTERVAL (H)		
	24	48	72
INTERCEPT	2.7082	4.8142	5.9913
UOLD2	.0	0.3399	0.2099
UOLD3	0.2632	.0	.0
VOLD3	-0.4945	-0.3005	-0.2596
DISP2	0.0256	.0	.0
CU1	0.2820	0.2456	0.2643
CU2	0.7176	0.6637	0.6653
CU6	.0	.0	-0.5090
CU7	.0	0.3342	0.5877
CU8	-0.3730	.0	-0.3206
CU14	.0	-0.6074	.0
CU16	.0	0.5874	.0
CU18	.0	.0	-0.6714
CU23	.0	.0	0.6666
CU24	.0	.0	-0.7699
CU26	.0	-0.7092	-1.1047
CU27	.0	.0	1.0278
CV1	-0.3872	.0	.0
CV2	.0	0.3031	.0
CV4	-0.3112	-0.4360	.0
CV7	.0	0.3937	0.3179
CV23	.0	.0	0.6105
CV28	0.7880	.0	.0

TABLE IX

Sample size and R^2 by forecast time and level for the zonal and meridional equations.

	FORECAST INTERVAL (H)		
	24	48	72
NUMBER OF DEPENDENT CASES	409	308	232
	ZONAL EQUATIONS		
700 mb	0.647	0.708	0.637
400 mb	0.612	0.637	0.613
250 mb	0.623	0.607	0.589
	MERIDIONAL EQUATIONS		
700 mb	0.475	0.439	0.447
400 mb	0.492	0.408	0.336
250 mb	0.481	0.440	0.325

TABLE X

Means and standard deviations of the predictands (km/h) for the dependent sample.

	FORECAST INTERVAL (H)		
	24	48	72
	ZONAL AVERAGE SPEED		
MEAN	8.2	8.9	9.6
STANDARD DEVIATION	14.1	11.8	10.3
	MERIDIONAL AVERAGE SPEED		
MEAN	8.6	8.3	7.8
STANDARD DEVIATION	8.0	6.7	5.7

TABLE VIII

Potential predictors for regression analysis.

POTENTIAL PREDICTOR VARIABLE NUMBER	NAME	DESCRIPTION
1	DATE	Julian date.
2	CLAT	Warning position latitude.
3	CLON	Warning position longitude.
4	CINT	Maximum sustiained wind speed (kts).
5	UOLD1	Average zonal cyclone movement from 24 to 12 h before base time (m/s).
6	UOLD2	Average zonal cyclone movement for 12 h before base time (m/s).
7	UOLD3	Average zonal cyvlone movement for 24 h before base time (m/s).
8	VOLD1	Average meridional cyclone movement from 24 to 12 h before base time (m/s).
9	VOLD2	Average meridional cyclone movement for 12 h before base time (m/s).
10	VOLD3	Average meridional cyclone movement for 24 h before base time (m/s).
11	DISP1	Vector displacement for 24 to 12 h before base time (m).
12	DISP2	Vector displacement for 12 h before base time (m).
13	DISP3	Vector displacement for 24 h before base time (m).
14 to 48	CU1 to CU35	EOF coefficients derived for zonal modes 1 to 35.
49 to 83	CV1 to CV35	EOF coefficients derived for meridional modes 1 to 35.

TABLE VI

Summary of the number of modes retained and percentage of variance described (in parentheses).

	ZONAL	MERIDIONAL
700 mb	24 (84.7)	35 (81.7)
400 mb	21 (86.0)	33 (82.4)
250 mb	19 (87.0)	29 (82.0)

TABLE VII

Percentages of variance accounted for when 35 modes are retained for all wind component fields.

	ZONAL	MERIDIONAL
700 mb	90.0	81.7
400 mb	92.1	83.6
250 mb	93.2	85.4

TABLE V

Mean eigenvalues and 95 percent confidence levels as computed by the Monte Carlo technique.

MODE	MEAN EIGENVALUE	MEAN EIGENVALUE PLUS TWICE THE STANDARD DEVIATION
1	3.424	4.116
2	3.318	3.989
3	3.299	3.966
4	3.261	3.919
5	3.228	3.880
6	3.211	3.859
7	3.192	3.837
8	3.139	3.773
9	3.110	3.738
10	3.101	3.728
11	3.086	3.710
12	3.048	3.664
13	3.031	3.643
14	2.986	3.589
15	2.970	3.570
16	2.963	3.561
17	2.930	3.522
18	2.917	3.507
19	2.900	3.486
20	2.872	3.452
21	2.850	3.425
22	2.816	3.385
23	2.808	3.375
24	2.797	3.362
25	2.774	3.334
26	2.766	3.325
27	2.743	3.297
28	2.723	3.273
29	2.697	3.242
30	2.681	3.222
31	2.663	3.200
32	2.643	3.177
33	2.636	3.168
34	2.627	3.158
35	2.619	3.149
36	2.591	3.114
*		
100	1.817	2.184
*		
300	0.569	0.684
*		
400	0.238	0.286
*		
527	0.016	0.019

TABLE IV

250 mb component wind fields: eigenvalues and cumulative percentage of variance (in parentheses).

MODE	250 mb ZONAL		250 mb MERIDIONAL	
1	160.599	(30.5)	62.690	(10.0)
2	84.874	(46.7)	49.187	(19.4)
3	48.568	(55.9)	41.620	(27.3)
4	31.797	(61.9)	28.325	(32.7)
5	21.493	(66.0)	26.942	(37.8)
6	16.544	(69.2)	24.028	(42.3)
7	13.239	(71.7)	20.635	(46.3)
8	11.062	(73.8)	18.627	(49.8)
9	9.858	(75.6)	16.555	(53.0)
10	9.373	(77.4)	15.219	(55.8)
11	8.456	(79.0)	12.888	(58.3)
12	7.832	(80.5)	12.162	(60.6)
13	6.523	(81.8)	11.283	(62.8)
14	5.982	(82.9)	10.369	(64.7)
15	5.147	(83.9)	10.050	(66.6)
16	4.687	(84.8)	8.838	(68.3)
17	4.287	(85.6)	8.253	(69.9)
18	4.004	(86.3)	7.214	(71.3)
19	3.625	(87.0)	6.815	(72.5)
20	3.299	(87.7)	6.808	(73.8)
21	2.974	(88.2)	6.203	(75.0)
22	2.812	(88.8)	5.883	(76.1)
23	2.661	(89.3)	5.232	(77.1)
24	2.369	(89.7)	4.881	(78.1)
25	2.234	(90.1)	4.361	(78.9)
26	2.070	(90.5)	4.416	(79.8)
27	2.061	(90.0)	4.074	(80.6)
28	1.897	(91.3)	3.870	(81.3)
29	1.703	(91.6)	3.533	(82.0)
30	1.610	(91.9)	3.410	(82.6)
31	1.542	(92.2)	3.212	(83.2)
32	1.420	(92.5)	3.121	(83.8)
33	1.354	(92.7)	2.950	(84.4)
34	1.339	(93.0)	2.858	(84.9)
35	1.266	(93.2)	2.566	(85.4)
36	1.212	(93.5)	3.121	(83.8)
*				
100	0.146	(98.7)	0.314	(97.2)
*				
300	0.004	(99.9)	0.009	(99.9)
*				
527	0.000	(100.)	0.000	(100.)

TABLE III

400 mb component wind fields: eigenvalues and cumulative percentage of variance (in parentheses).

MODE	400 mb ZONAL		400 mb MERIDIONAL	
1	132.856	(25.3)	47.827	(9.1)
2	86.314	(41.7)	44.391	(17.5)
3	45.448	(50.3)	28.707	(23.0)
4	30.134	(56.0)	26.999	(28.1)
5	24.910	(60.8)	24.486	(32.8)
6	17.362	(64.1)	22.029	(37.0)
7	14.977	(66.9)	20.417	(40.8)
8	13.151	(69.4)	19.241	(44.5)
9	10.865	(71.5)	16.344	(47.6)
10	9.788	(73.3)	15.236	(50.5)
11	8.807	(75.0)	14.514	(53.3)
12	8.504	(76.6)	13.844	(55.9)
13	7.924	(78.1)	12.340	(58.2)
14	6.862	(79.4)	11.115	(60.3)
15	6.406	(80.6)	10.677	(62.4)
16	6.091	(81.8)	9.888	(64.3)
17	5.738	(82.9)	8.965	(66.0)
18	4.839	(83.8)	7.820	(67.4)
19	4.181	(84.6)	7.768	(68.9)
20	3.727	(85.3)	6.984	(70.2)
21	3.630	(86.0)	6.562	(71.5)
22	3.276	(86.6)	6.366	(72.7)
23	3.101	(87.2)	6.065	(73.9)
24	2.938	(87.8)	5.548	(74.9)
25	2.670	(88.3)	5.456	(75.9)
26	2.653	(88.8)	5.351	(77.0)
27	2.522	(89.3)	4.798	(77.9)
28	2.385	(89.7)	4.452	(78.7)
29	2.155	(90.1)	4.201	(79.5)
30	1.984	(90.5)	4.071	(80.3)
31	1.816	(90.8)	3.885	(81.0)
32	1.772	(91.2)	3.746	(81.7)
33	1.703	(91.5)	3.478	(82.4)
34	1.534	(91.8)	3.278	(83.0)
35	1.509	(92.1)	3.063	(83.6)
36	1.437	(92.4)	2.924	(84.2)
*				
100	0.152	(98.6)	0.340	(97.0)
*				
300	0.004	(99.9)	0.009	(99.9)
*				
527	0.000	(100.)	0.000	(100.)

TABLE II

700 mb component wind fields: eigenvalues and cumulative percentage of variance (in parentheses).

MODE	700 mb ZONAL		700 mb MERIDIONAL	
1	95.157	(18.1)	41.438	(7.9)
2	72.772	(31.9)	38.417	(15.2)
3	44.161	(40.3)	29.189	(20.7)
4	34.540	(46.9)	25.566	(25.6)
5	31.632	(52.9)	24.171	(30.2)
6	20.146	(56.7)	20.959	(34.2)
7	16.750	(59.9)	19.123	(37.8)
8	15.459	(62.8)	18.485	(41.3)
9	13.343	(65.4)	16.477	(44.4)
10	12.325	(67.7)	15.751	(47.4)
11	10.354	(69.7)	14.613	(50.2)
12	9.312	(71.5)	12.695	(52.6)
13	8.989	(73.2)	11.757	(54.9)
14	8.417	(74.8)	11.478	(57.0)
15	7.488	(76.2)	10.429	(59.0)
16	6.715	(77.5)	10.171	(61.0)
17	6.390	(78.7)	9.090	(62.7)
18	5.701	(79.8)	8.595	(64.3)
19	5.173	(80.7)	8.424	(65.9)
20	4.931	(81.7)	7.539	(67.4)
21	4.373	(82.5)	7.136	(68.7)
22	4.244	(83.3)	7.011	(70.0)
23	3.801	(84.0)	6.492	(71.3)
24	3.445	(84.7)	5.816	(72.4)
25	3.244	(85.3)	5.688	(73.5)
26	3.174	(85.9)	5.518	(74.5)
27	2.839	(86.5)	5.103	(75.5)
28	2.790	(87.0)	4.865	(76.4)
29	2.663	(87.5)	4.611	(77.3)
30	2.482	(88.0)	4.405	(78.1)
31	2.403	(88.4)	4.254	(78.9)
32	2.237	(88.8)	4.070	(79.7)
33	2.205	(89.3)	3.751	(80.4)
34	1.990	(89.6)	3.445	(81.1)
35	1.913	(90.0)	3.207	(81.7)
36	1.809	(90.4)	3.039	(82.3)
*				
100	0.206	(98.2)	0.397	(96.4)
*				
300	0.005	(99.9)	0.012	(99.9)
*				
527	0.000	(100.)	0.000	(100.)

APPENDIX B

TABLES

TABLE I

Operational models for the prediction of tropical cyclone motion over the North Atlantic.*

MODEL	TYPE MODEL	DESCRIPTION
HURRAN	STATISTICAL	Analog model based on tracks of all Atlantic tropical cyclones since 1886. (Operational 1968)
CLIPER	STATISTICAL	Regression equation model utilizing predictors derived from climatology and persistence. (Operational 1971)
NHC67	STATISTICAL-SYNOPTIC	Regression equation model utilizing predictors derived from climatology persistence and observed geopotential height data. (Operational 1967)
NHC72	STATISTICAL-SYNOPTIC	Regression equation model utilizing predictors derived from output of CLIPER model and observed geopotential height data. (Operational 1972)
NHC73	STATISTICAL-DYNAMICAL	Regression equation model utilizing predictors derived from output of CLIPER model, observed and numerically forecast geopotential height data. (Operational 1973)
SANBAR	DYNAMICAL	Barotropic model based on pressure-weighted wind field averaged through troposphere and represented on a 154 km (at 22.5 N) spaced grid. (Operational 1970)
MFM	DYNAMICAL	Movable Fine Mesh (MFM) baroclinic model having 10 levels in the vertical and 60 km grid spacing in the horizontal. (Operational 1976)

* (from Neumann and Pelissier, 1981)

TABLE XVII

Mean and standard deviation (km) forecast vector errors for the dependent sample.

	FORECAST INTERVAL (H)		
	24	48	72
NUMBER OF DEPENDENT DATA CASES	409	308	232
	MEAN VECTOR ERROR		
700 mb	200.7	351.7	465.8
400 mb	189.3	349.0	453.7
250 mb	204.0	365.4	491.6
	STANDARD DEVIATION		
700 mb	134.9	217.2	256.1
400 mb	131.5	225.2	297.8
250 mb	138.0	231.7	158.2

BIBLIOGRAPHY

Anderson, T. W., 1963: The use of factor analysis in the statistical analysis of multiple time series. Psychometricka, 28, 1-25.

Barnett, T. P., 1977: The principal time and space scales of the Pacific trade wind fields. Journal of the Atmospheric Sciences, 34, 221-236.

Brown, D. W., 1981: Tropical storm movement forecasting based on synoptic map typing using Empirical Orthogonal Functions. M. S. Thesis, Naval Postgraduate School, Monterey, CA, 80pp.

Cattell, R. B., 1958: Extracting the correct number of factors in factor analysis. Educational and Psychological Measurement, 18, 791-837.

Chan, J. C. L., and W. M. Gray, 1982: Tropical cyclone movement and surrounding flow relationships. Monthly Weather Review, 110, 1354-1374.

Chan, J. C. L., W. M. Gray, and S. Q. Kidder, 1980: Forecasting tropical cyclone turning motion from surrounding wind and temperature fields. Monthly Weather Review, 108, 778-792.

Chen, L., and W. M. Gray, 1984: Global view of the upper level outflow patterns associated with tropical cyclone intensity changes during FGGE. Postprints, 15th Conference on Hurricanes and Tropical Meteorology, January 9-13, Miami, Florida, 224-231.

Dixon, W. J., and M. B. Brown, 1979: BMDP Biomedical Computer Program P-Series, University of California Press, Berkley California, pp. 367-460.

George, J. E., and W. M. Gray, 1976: Tropical cyclone motion and surrounding parameter relationships. Journal of Applied Meteorology, 15, 1252-1264.

Gray, W. M., 1978: Reply. Journal of Applied Meteorology, 17, 419-420.

Gray, W. M., 1979: Hurricanes: their formation, structure and likely role in the tropical circulation. Meterology over the Tropical Oceans. D. B. Shaw (Ed.), Royal Meteorological Society, Bracknell, Great Britain, 155-218.

Graybill, F. A., 1976: Theory and Application of the Linear Model, Duxbury Press, 704 pp.

Grimmer, M., 1963: The space-filtering of monthly surface temperature data in terms of patterns, using empirical orthogonal functions. Quarterly Journal of the Royal Meteorological Society, 39, 395-408.

Guttman, L., 1954: Some necessary conditions for common factor analysis. Psychometricka, 19, 149-161.

Haltiner, G. J., and R. T. Williams, 1980: Numerical Weather Prediction and Dynamic Meteorology, John Wiley and Sons (ed. 2), 476 pp.

Hardy, D. M., 1977: Empirical eigenvector analysis of vector observations. Geophysical Research Letters, 4, 319-320.

Hardy, D. M., and J. J. Walton, 1978: Principal components analysis of vector wind measurements. Journal of Applied Meteorology, 17, 1153-1162.

Hope, J. R., and C. J. Neumann, 1970: An operational technique for relating the movement of existing tropical cyclones to past tracks. Monthly Weather Review, 98, 925-933.

Jarrel, J. D., S. Brand and D. S. Nicklin, 1978: An analysis of western North Pacific tropical cyclone forecast errors. Monthly Weather Review, 106, 925-937.

Joint Typhoon Warning Center, 1983: Annual Tropical Cyclone Report. U. S. Fleet Weather Central, Joint Typhoon Warning Center, Guam, COMNAVMARINAS, Box 17, FPO San Francisco 96630.

Jordan, E. S., 1952: An observational study of the upper wind circulation around tropical storms. Journal of Meteorology, 14, 386-402.

Kjelass, A. G., and others, 1971: Statistical Methods and Instrumentation in Geophysics. Teknologisk Forlag, Oslo, 337 pp.

Kutzbach, J. E., 1967: Empirical eigenvectors of sea-level pressure, surface temperature and precipitation complexes over North America. Journal of Applied Meteorology, 6, 791-802.

Legler, D., 1983: Empirical Orthogonal Function Analysis of Wind Vectors over the Tropical Pacific Region. Bulletin of the American Meteorological Society, 64, 234-241.

Ley, G. W., and R. L. Elsberry, 1976: Forecasts of Typhoon Irma using a nested-grid model. Monthly Weather Review, 104, 1154-1161.

Lorenz, E. N., 1956: Empirical Orthogonal Functions and statistical weather prediction. Massachusetts Institute of Technology Department of Meteorology, Cambridge, Massachusetts. Scientific Report 1, Statistical Forecasting Project, 48 pp.

Mateer, C. L., 1965: On the information content of umkehr observations. Journal of the Atmospheric Sciences, 22, 370-381.

Miller, B. I., 1958: The use of mean layer winds as a hurricane steering mechanism. National Hurricane Research Project Report No. 18, 24 pp.

Miller, B. I., and P. L. Moore, 1960: A comparison of hurricane steering levels. Bulletin of the American Meteorological Society, 41, 59-63.

Miller, B. I., P. P. Chase and B. R. Jarvinen, 1972: Numerical prediction of tropical weather systems. Monthly Weather Review, 100, 825-835.

Morrison, D. F., 1967: Multivariate Statistical Methods. McGraw-Hill (ed. 2, 1976), 338 pp.

Neter, J., and W. Wasserman, 1974: Applied Linear Statistical Models. Richard D. Irwin, Inc., Homewood, IL, 842 pp.

Neumann, C. J., 1978: Comments on "Tropical Cyclone Motion and Surrounding Parameter Relationships". Journal of Applied Meteorology, 17, 418-419.

Neumann, C. J., 1981: Trends in forecasting the tracks of Atlantic tropical cyclones. Bulletin of the American Meteorological Society, 62, 1473-1485.

Neumann, C. J., and M. B. Lawrence, 1973: Statistical-dynamical prediction of tropical cyclone motion (NHC73). NOAA Technical Memorandum NWS SR-69, 34 pp.

Neumann, C. J., and M. B. Lawrence, 1975: An operational experiment in the statistical-dynamical prediction of tropical cyclone motion. Monthly Weather Review, 103, 665-673.

Neumann, C. J., and J. M. Pelissier, 1981: Models for the prediction of tropical cyclone motion over the North Atlantic: an operational evaluation. Monthly Weather Review, 109, 522-538.

Neumann, C. J., and E. A. Randrianarison, 1976: Statistical prediction of tropical cyclone motion over the Southwest Indian Ocean. Monthly Weather Review, 104, 76-85.

Ooyama, K. V., 1982: Conceptual evolution of the theory and modeling of the tropical cyclone. Journal of the Meteorological Society of Japan, 60, 369-379.

Preisendorfer, R. W., and T. P. Barnett, 1977: Significance tests for empirical orthogonal functions. Proceedings from the 5th conference on Probability and Statistics in Meteorology and Atmospheric Science, Nov. 15-18, 1977, American Meteorological Society, Boston, MA, 169-172.

Renard, R. J., 1968: Forecasting the motion of tropical cyclones using a numerically derived steering current and its bias. Monthly Weather Review, 96, 453-469.

Renard, R. J., S. G. Colgan, M. J. Daley and S. K. Rinard, 1973: Forecasting the motion of North Atlantic tropical cyclones by the objective MOHATT scheme. Monthly Weather Review, 101, 206-214.

Richman, M. B., 1980: Map typing patterns associated with urban enhanced precipitation. M. S. Thesis, University of Illinois, Urbana, 123 pp.

Riehl, H., and R. J. Shafer, 1944: The recurvature of tropical storms. Journal of Meteorology, 1, 42-54.

Rinne, J., and V. Karhila, 1979: Empirical Orthogonal Functions of the 500 mb height in the Northern Hemisphere determined from a large data sample. Quarterly Journal of the Royal Meteorological Society, 105, 873-884.

Sanders, F., and R. W. Burpee, 1968: Experiments in barotropic hurricane track forecasting. Journal of Applied Meteorology, 7, 313-323.

Shaffer, A. R., 1982: Typhoon motion forecasting using empirical orthogonal function analysis of the synoptic forcing. M. S. Thesis, Naval Postgraduate School, Monterey, CA, 150 pp.

Shaffer, A. R., and R. L. Elsberry, 1982: A statistical-climatological tropical cyclone track prediction technique using an EOF representation of the synoptic forcing. Monthly Weather Review, 110, 1945-1954.

Shapiro, L. J., and C. J. Neumann, 1984: On the orientation of grid systems for the statistical prediction of tropical cyclone motion. Monthly Weather Review, 112, 188-199.

Stidd, C. K., 1967: The use of eigenvectors for climatic estimation. Journal of Applied Meteorology, 6, 255-264.

Tse, S. Y. W., 1966: A new method for the prediction of typhoon movement using the 700 mb chart. Quarterly Journal of the Royal Meteorological Society, 92, 239-254.

Wells II, L., 1982: Weather and darkness in contemporary naval operations. Proceedings/Naval Review, 108/5/95, 151-167.

INITIAL DISTRIBUTION LIST

		No. Copies
1.	Defense Technical Information Center Cameron Station Alexandria, VA 22314	2
2.	Library, Code 0142 Naval Postgraduate School Monterey, CA 93943	2
3.	Chairman (Code 63 Rd) Department of Meteorology Naval Postgraduate School Monterey, CA 93943	1
4.	Chairman (Code 68Mr) Department of Oceanography Naval Postgraduate School Monterey, CA 93943	1
5.	Professor Russell L. Elsberry (Code 63Es) Department of Meteorology Naval Postgraduate School Monterey, CA 93943	3
6.	LT William E. Wilson, USN NAVOCEANCOMCEN Box 12 FPO San Francisco, CA 96630	3
7.	Dr. Johnny C. L. Chan (Code 63Cd) Department of Meteorology Naval Postgraduate School Monterey, CA 93943	1
8.	Director Naval Oceanography Division Naval Observatory 34th and Massachusetts Avenue NW Washington, DC 20390	1
9.	Commander Naval Oceanography Command NSTL Station Bay St. Louis, MS 39522	1
10.	Commanding Officer Fleet Numerical Oceanography Center Monterey, CA 93940	1
11.	Commanding Officer Naval Environmental Prediction Research Facility Monterey, CA 93940	1
12.	Commander Air Weather Service Scott Air Force Base, IL 62225	1
13.	Commander (AIR-370) Naval Air Systems Command Washington, DC 20360	1

14. Commanding Officer 1
Naval Oceanography Command Center, Guam
Box 12
FPO San Francisco, CA 96630

15. Professor William M. Gray 1
Department of Atmospheric Science
Colorodo State University
Fort Collins, CO 80523

END

FILMED

7-85

DTIC